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Spatial diversification, dividend policy, and credit scoring in real estate

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SPATIAL DIVERSIFICATION, DIVIDEND POLICY, AND CREDIT SCORING IN REAL ESTATE

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Abstract

Built on the foundation of economic principles, real estate offers many pursuits of academic discovery within the realm of finance. This dissertation examines three areas of real estate finance. In the first chapter, I use the unique real estate characteristics of heterogeneity, immobility, and localized markets to examine the spatial aspects of large-scale commercial real estate portfolios. The results demonstrate a clear need for portfolio managers to diversify properties based upon distances between properties. The second chapter examines another large-scale real estate portfolio, the real estate investment trust, which is held by investors seeking dividend income. Despite the importance of dividend payouts to investors, current real estate literature does not fully explain the dividend policy of REITs. I find that REITs base dividend payouts on contemporaneous earnings, the level of dividends paid last period, and firm volatility. For real estate investors that desire income based upon debt instruments, the last chapter examines the prepayment and default of mortgage instruments using credit scoring. I address the research question of how credit scoring affects mortgage pricing. The findings indicate a need to include credit scores as a state variable in a mortgage option pricing model. Overall, each chapter furthers our understanding of real estate finance.

1. Introduction

Nongovernment real estate is a $22 trillion asset category, which exceeds the size of other common asset categories such as corporate equities (13 trillion), government debt (7 trillion), and mortgage debt (8 trillion). The magnitude of the market offers numerous avenues for real estate research. I explore three in this dissertation.

The first essay examines the spatial component of commercial real estate portfolio risk. Commercial properties exhibit spatial correlation when properties are located in close proximity to one another. I find that separation distance between properties is important within metropolitan submarkets. Further, when I control for the rural regions inherent in a U.S. national study, I find statistically significant positive autocorrelation in 12 of 15 Consolidated Metropolitan Statistical Areas. Overall, the results in the first chapter demonstrate that commercial real estate portfolio should consider the spatial correlation of properties held within a Metropolitan Statistical Areas.

The second chapter addresses questions about agency costs, dividend policies, and dividend smoothing in Real Estate Investment Trusts (REITs). Two papers frame much of the general understanding of dividend payouts by REITs. The REIT is a unique organizational structure because tax law requires 90 percent of taxable earnings must be paid to shareholders. Our current understanding is that REITs show a negative correlation between the return on assets ratio and dividend payout. The amount of debt versus total company assets is also explanatory in explaining dividend policy. I find that REITs exhibit correlations between dividend policy and proxies for agency costs and asymmetric information when simultaneity is a concern. By controlling for endogeneity, autocorrelation, and heteroscedasticity, I find that the dividend policy of REITs is dictated by contemporaneous earnings, the level of dividends paid last period, and a proxy for firm volatility. These findings coincide with discussion in the literature regarding the many favorable REIT attributes that control for market imperfections.

The last essay investigates credit scoring in mortgages. Credit scores are instrumental in lenders' decisions concerning mortgage accessibility and interest rate levels. To date, mortgage pricing models structure credit scores as a transaction cost or friction in the market. I posit that credit scores are a competing transaction cost, which means that a change in a borrower's credit score affects both the prepayment and default options of a mortgage. This leads to changes in the pricing of the mortgage.

Overall, real estate offers many facets of academic discovery. Built on economic and finance understanding, real estate offers uniqueness within the finance field due to heterogeneous products that are immobile and localized. I examine these specific elements in the next section regarding real estate portfolios.

2. Real Estate Portfolios

Modern portfolio theory, as pioneered by Markowitz (1952), demonstrates that diversification can increase the return for a given variance or reduce the risk for a given return. Further, individual investors can diversify their own portfolios to generate the desired return for a preferred risk in perfect capital markets. Portfolio managers have no advantage in providing diversification in the absence of restrictions and bankruptcy costs.

Diversification of a portfolio that directly owns real estate assets, however, is more complex. Institutions and pension funds have been making direct real estate investments for decades due to depreciation and tax benefits, low volatility, and income generation. But real estate portfolio managers face a trade-off. On one hand, due to the local nature of real estate, a portfolio manager will want to specialize within a market or region. By specializing, a manager can become an expert in the local market and reduce search and on-going portfolio costs. On the other hand, due to the immobility of land, diversification of a real estate portfolio requires investments across diverse markets. By holding multiple properties within a submarket or Metropolitan Statistical Area (MSA), real estate portfolios will experience a correlation of property returns due to a lack of distance between the holdings. Neighboring properties will experience similar supply and demand conditions, property tax regimes, labor markets, as well as zoning laws.

In this study, I examine the spatial component of commercial real estate portfolios by joining portfolio theory with the tools of spatial econometrics. While previous studies have identified the importance of geographic diversification within real estate portfolios -- with the regions of study advancing from four or eight U.S. zones to Metropolitan Statistical Areas (MSAs) to neighborhoods within a city – the literature does not use spatial tools for systematic examination of spatial dependence among real estate properties. It is not surprising that nearby properties exhibit a degree of spatial dependence, but research questions exist regarding i) how much initial spatial correlation is present for adjacent properties, especially for different commercial property types since diversification by property type is effective is other real estate diversification studies; ii) how quickly does the spatial correlation decay; and iii) at what distance does the spatial correlation decay to zero. The last question is of particular importance since zero spatial correlation implies mitigation of spatial portfolio risk.

To address the research questions, I employ spatial econometric methods to measure correlations of property attributes as a function of the distance between the properties. The results demonstrate significant spatial correlations for properties separated from 0 to 40 miles. Overall, commercial real estate exhibits significant spatial correlation within MSAs and across multiple MSAs that are within a larger metropolitan region. Portfolio diversification by property type is helpful in reducing the spatial correlation, however, the effect is minimal if the location of the properties is within the same or adjacent zip codes.

In general, the distance to reach random spatial correlation coincides roughly with the diameter of many MSAs. The empirical results and subsequent simulations imply a sufficient condition of building a commercial real estate portfolio is a strategy that holds one property per MSA or Consolidated MSA (CMSA). Owning different types of property within an MSA reduces correlation, but not fully. Also, adding more properties within an MSA is not particularly helpful. Unlike Fama (1976), where the portfolio standard deviation of an equally weighted portfolio of equity securities decays to about zero with a portfolio of fifteen randomly selected stocks, adding more properties within an MSA or CMSA potentially compounds the spatial correlation problem. Overall, the results demonstrate a need for portfolio managers to separate portfolio properties across MSAs.

The remainder of this chapter proceeds as follows. Section 2.1 discusses previous real estate diversification studies and applications of spatial techniques in the real estate literature. Section 2.2 examines spatial correlation and portfolio theory. Section 2.3 details the spatial tools for this study. Section 2.4 presents findings from various commercial property datasets. Section 2.5 details the findings for residential returns. Section 2.6 presents combined commercial and residential property findings. Section 2.7 applies the empirical results to the portfolio theory in section 2. Lastly, section 2.8 summarizes this chapter.

2.1 Diversification and Spatial Literature

Diversification of real estate portfolios is the subject of considerable research over the past two decades. The two predominant paths of analysis are diversification either by property type or by geographic or economic regions. Initially, Miles and McCue (1982) find that diversification by property type generates better characteristics than a strategy based upon geographic regions. Subsequent studies, such as those by Hartzell, Hekman, and Miles (1986), Hartzell, Shulman, and Wurtzebach (1987), Mueller and Ziering (1992), Mueller (1993), Goetzmann and Wachter (1995), Williams (1996), Wolverton, Cheng and Hardin (1998), as well as Cheng and Black (1998), redefine the geographic categories into either more minute areas or based upon economic strategies such as Standard Industrial Classification groups. Overall, the research establishes that geographic grouping based upon economic characteristics is dominant over geographic division based upon political boundaries (e.g., state borders), and smaller regions such as MSAs or neighborhoods are more appropriate for diversification than four or eight national regions.

Explicit or implicit in these studies is a search for homogeneous regions such that correlations between regions can be computed to diversify away unsystematic portfolio risk. A concern with establishing a region ex ante is that real estate functions in a local market, and even within a small region, such as an MSA, multiple geographic regions may exist that covary to some degree. To address the issue of homogeneous regions, this study measures the correlation between properties, not as a function of geographic, political, or economic boundaries, but as a function of separation distance between properties.

The application of separation distance and spatial econometrics is new to commercial real estate, however, prior use of spatial econometrics is found in the residential market literature. Dubin (1992) uses a method of spatial prediction on single-family property transactions in Baltimore to compute house price contours. Can (1992) and Can and Megbolugbe (1997) examine spatial autocorrelation in house prices by including spatially lagged values of the response variable in a hedonic model. Basu and Thibodeau (1998) examine spatial correlation in Dallas house prices and find spatial techniques generally improve OLS. Thibodeau (2003) uses spatial econometrics to examine the increase in prediction accuracy for within-metropolitan-area housing submarkets. And more recently, the September, 2004 volume of *The Journal of Real Estate Finance and Economics* presents four papers applying spatial techniques to the housing market. In general, the importance of spatial econometrics is evolving in the real estate literature. In the next section, I motivate the use of spatial econometrics within a commercial real estate portfolio.

2.2 Spatial Correlation and Portfolio Theory

2.2.1 Portfolio Risk

To determine how spatial correlation fits into general portfolio theory, consider a portfolio of *N* risky assets. The risk of the portfolio is a function of the variance of each asset and the covariance between the assets. Assuming that the portfolio is equally weighted such that the weight, *w*, of each asset is $w_i = w_j = 1/N$, then the portfolio risk or variance, σ_p^2, is

$$\sigma_p^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} \frac{1}{N}\frac{1}{N}\sigma_{ij} = \frac{1}{N^2}\sum_{i=1}^{N} \sum_{j=1}^{N}\sigma_{ij} ,$$

where N is the number of risky assets in the portfolio, and σ_{ij} is the covariance between each risky asset. By definition, the covariance is

$$\sigma_{ij} = \sigma_i \sigma_j \rho(i, j),$$

where $\sigma_i \sigma_j$ is the product of the standard deviations and $\rho(i, j)$ is the correlation between assets i and j. Further, without loss of generality, if I let $\sigma_i = \sigma_j = 1$, then the variance of the portfolio expressed as a function of correlation is

$$\sigma_p^2 = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{\substack{j=1 \\ i \neq j}}^{N} \rho_{ij} \ . \tag{1}$$

It follows that as N increases, the portfolio variance approaches the average correlation. Thus, the risk of a real estate portfolio is a function of the correlations between the properties.

2.2.2 Spatial Source of Portfolio Risk

To better understand the spatial component of the portfolio correlation function, begin with two risky assets, noting that systematic risk is a measure of how an asset covaries with the economy and unsystematic risk is independent of the economy. Since the return on any risky asset is a linear function of the market return plus a random error term, $\tilde{\varepsilon}$, the return generating equations of two risky assets i and j are

$$\tilde{R}_i = a_i + b_i \tilde{R}_m + \tilde{\varepsilon}_i$$

and

$$\tilde{R}_j = a_j + b_j \tilde{R}_m + \tilde{\varepsilon}_j \ .$$

The assumption in portfolio theory is that the error term of a specific risky asset, j, is independent of the market. This fact implies that $COV(\tilde{R}_m, \tilde{\varepsilon}_j) = 0$. Thus, the portfolio risk, expressed as $COV(R_i, R_j) = \mathrm{E}(R_i R_j) - \mathrm{E}(R_i)\mathrm{E}(R_j)$, is

$$COV(R_i, R_j) = \mathrm{E}\left[(a_i + b_i R_m)(a_j + b_j R_m)\right] - (a_i + b_i \mathrm{E}(R_m))(a_j + b_j \mathrm{E}(R_m))$$

$$= \mathrm{E}(a_i a_j + a_i b_j R_m + a_j b_i R_m + b_i b_j R_m^2) - (a_i a_j + a_i b_j \mathrm{E}(R_m) + a_j b_i \mathrm{E}(R_m) + b_i b_j \mathrm{E}(R_m)^2)$$

$$= b_i b_j \left[\mathrm{E}(R_m^2) - \mathrm{E}(R_m)^2\right]$$

$$= b_i b_j \sigma_m^2 . \qquad (2)$$

The result is the systematic portion of portfolio risk.

What if the assumption of $COV(\tilde{R}_m, \tilde{\varepsilon}_j) = 0$ does not hold? Real estate portfolios add another dimension not found in portfolios consisting of nonspatial financial assets. The spatial dimension introduces correlation into the random error terms, resulting in the covariance between two risky properties of

$$COV(R_i, R_j) = b_i b_j \sigma_m^2 + b_i \mathrm{E}(R_m \varepsilon_j) - b_i \mathrm{E}(R_m)\mathrm{E}(\varepsilon_j) + b_j \mathrm{E}(R_m \varepsilon_i)$$

$$-b_j \mathrm{E}(R_m)\mathrm{E}(\varepsilon_i) + \mathrm{E}(\varepsilon_i \varepsilon_j) - \mathrm{E}(\varepsilon_i)\mathrm{E}(\varepsilon_j) \qquad (3)$$

Since the differences between equations (2) and (3) are spatially diversifiable, I contend that the extra terms in equation (3) represent unsystematic risk. The implication for a real estate portfolio is that properties need to be spaced sufficiently far apart for $COV(\tilde{R}_m, \tilde{\varepsilon}_j) = 0$ to hold. To better quantify the intuition of sufficiently separated, the next section examines some spatial tools to measure the spatial correlation.

2.3 The Variogram and Correlogram

The portion of geostatistics I use for this study focuses on the continuous nature of a series of return observations y_i, $i=1,...,N$, over a national study region $\mathbb{R}$, the contiguous United States. The returns are assumed to be observations on a spatial stochastic process $\{Y(s), s \in \mathbb{R}\}$, which varies in a spatially continuous manner over $\mathbb{R}$ and has been sampled at fixed points.

Bailey and Gatrell (1995) build a mathematical foundation for the correlogram as follows. If there exists a spatially stochastic process $\{Y(s), s \in \mathbb{R}\}$ where the expected value of $Y(s)$ is $\mu(s)$ and $VAR[Y(s)]$ is $\sigma^2(s)$ then the covariance of this process at any two points s_i and s_j is defined as

$$C(s_i, s_j) = \mathrm{E}\left[(Y(s_i) - \mu(s_i))(Y(s_j) - \mu(s_j))\right]$$

with the corresponding correlation defined as

$$\rho(s_i, s_j) = \frac{C(s_i, s_j)}{\sigma(s_i)\sigma(s_j)}.$$

A spatially stochastic process is stationary if $\mu(s) = \mu$ and $\sigma^2(s) = \sigma^2$. Stationarity implies that the distribution of the mean or variance is invariant under translation. Thus, for a spatially stochastic process, the stationary random function is homogeneous in space. And for any increment of distance, the distributions of the mean and variance, or any other moments, are independent of location and constant throughout $\mathbb{R}$.

The distance between the two points s_i and s_j is the simple Euclidean geographic distance, denoted as *h*, a (Nx1) column vector. Therefore, the location of any one point is described by x_i and y_i coordinates as expressed in latitude and longitude measurements. Thus, two or more locations can be described by vectors of latitude and longitude values yielding $n(n-1)/2$ empirical data.

Since stationarity is assumed, the covariance of the spatially stochastic process can be reduced to

$$C(s_i, s_j) = C(s_i - s_j) = C(h).$$

Therefore, $C(s_i, s_j)$ depends only on the distance difference between s_i and s_j and not on the absolute locations. $C(h)$ is referred to as the covariance function or the variogram and $\rho(h)$ as the corresponding correlation function or correlogram.

On both theoretical and practical application it is acceptable to weaken the hypothesis of strict stationarity. Matheron (1963, 1965) developed intrinsic stationarity, which assumes that the increments of the spatially stochastic process are weakly stationary. Intrinsic stationarity implies that the mean and variance exist and are independent of the location. Thus

$$\mathrm{E}\left[Y(s+h)-Y(s)\right]=0$$

and

$$VAR\left[Y(s+h)-Y(s)\right]=2\gamma(h).$$

The function $2\gamma(h)$ is termed a semi-variogram. The variogram is one-half of the semi-variogram. For stationary and intrinsic attributes, the mean of $Y(s+h)-Y(s)=0$ thus let $\gamma(h)$ be the mean square difference as defined by

$$\gamma(h)=\frac{1}{2}\mathrm{E}\left[Y(s+h)-Y(s)\right]^2$$

and the method of moment estimator of an experimental variogram is

$$\hat{\gamma}(h)=\frac{1}{2N(h)}\sum_{i=1}^{N(h)}\left[Y(s+h)-Y(s)\right]^2,$$

where the summation is over all pairs of observed data points with a vector of separation *h* and *N(h)* is the number of difference pairs. Note that when the distance difference vector is null, theoretically the sample estimator is equal to 0. Additionally, the variogram is symmetric in *h*. Figure 1 presents the general form of the variogram.

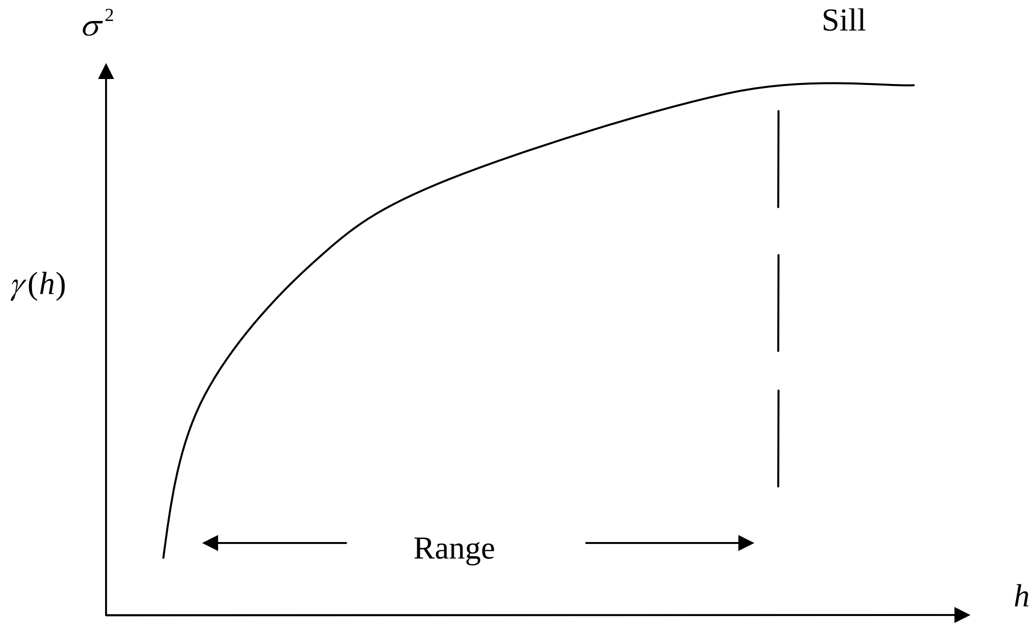

Figure 1: General Shape of a Bounded Variogram.

Although theoretically $\hat{\gamma}(0) = 0$, small-scale variability may cause sample values with small separations to be disparate. This causes a discontinuity at the origin of the experimental variogram, which is termed the *nugget*. A real estate example of the nugget is the covariance of two residential properties adjacent to each other. After controlling for the size of home, the year built and other explanatory variables, the homes could still exhibit a high spatial correlation because of their close proximity.

In the earth sciences, the actual distances of *h* may be quite uniform. For example, the correlogram of an underground mineral deposit may be computed using readings from holes drilled beginning at the most southern and western point of the sample plot and continued every five yards in both a northerly and easterly direction. This will result in a uniform plot of sample readings along with a separation vector *h* that will have variogram or correlogram values for *h*=5,

h=10, etc. In applying the correlogram to national real estate returns, which consists of irregularly spaced sample points, there will rarely be observations with an exact vector separation of h. Therefore, intervals, known as lags, are created such that

$$\hat{\gamma}(h) = \frac{1}{2N(h)} \sum_{h_{ij} \approx h}^{N(h)} \left[Y(s+h) - Y(s) \right]^2 .$$

The average of the values that fit within the lag is used as the variogram or correlogram value at distance h. To account for observations that are on the edge of lags, a lag tolerance is often employed. The use of a lag tolerance results in values that lie outside the lag distance being included in the variogram and correlogram calculations. This produces a smoothing effect and eliminates some of the arbitrary judgment of how large to establish the lag. The number of lags is adjusted to ensure at least 30 to 50 observations in each lag. The maximum tolerance is 50 percent of the lag distance.

To compare dissimilarly-scaled variograms, the experimental variogram is standardized such that

$$\hat{\gamma}_s(h) = \frac{\hat{\gamma}(h)}{(\sigma_{-h})(\sigma_{+h})}$$

where $\hat{\gamma}(h)$ is the variogram from the separation vector h, and

$$\sigma_{-h}^2 = \frac{1}{N(h)} \sum_{h_{ij} \approx h}^{N(h)} Y^2(s_i) - m_{-h}^2 \text{, where } m_{-h} = \frac{1}{N(h)} \sum_{h_{ij} \approx h}^{N(h)} Y(s_i)$$

and

$$\sigma_{+h}^2 = \frac{1}{N(h)} \sum_{h_{ij} \approx h}^{N(h)} Y^2(s_i) - m_{+h}^2 \text{, where } m_{+h} = \frac{1}{N(h)} \sum_{h_{ij} \approx h}^{N(h)} Y(s_i) .$$

Division by the standard deviation of the s_i and s_j values within each lag rescales the variogram by the lag variance. Again, the standardized variogram is symmetric in h. For an omnidirectional variogram (i.e., variogram without regard for direction between observations), the standardized variogram and correlogram are linked as $\hat{\rho}(h) = 1 - \hat{\gamma}_s(h)$.

2.3.1 The Experimental Cross-Correlogram

An extension of the empirical correlogram is the empirical cross-correlogram. Spatial econometric methods provide the possibility of mutual estimation of multiple interconnected data. The cross-correlogram is used in this study to establish mutual correlation between the interconnected data of residential and commercial real estate returns.

Similar to the aforementioned correlogram, if $\{Y(s), s \in \mathbb{R}\}$ is the process relating to the first variable and $\{X(s), s \in \mathbb{R}\}$ is the process relating to the second variable, and both of these processes are assumed to be at least intrinsically stationary, then the cross-variogram is defined as

$$C_{YX}(h) = \mathrm{E}\left[(Y(s+h) - \mu_Y)(X(s+h) - \mu_X)\right],$$

where *h* is an arbitrary vector separation in $\mathbb{R}$. I can extend the same mathematical derivation mentioned previously to a cross-variogram, which is defined as

$$2\gamma_{YX}(h) = \mathrm{E}\left[(Y(s+h) - Y(s))(X(s+h) - X(s))\right].$$

The sample estimator of the cross-variogram, given *n* pairs of observations (y_i, x_i) at sample sites s_i and s_j is

$$\hat{\gamma}(h) = \frac{1}{2N(h)} \sum_{s_i - s_j = h}^{N(h)} (y_i - y_j)(x_i - x_j),$$

where the summation is over all pairs of observed data with a separation vector of *h* and *N(h)* number of pairs. Again, as in the estimation of the correlogram, real estate returns will not yield an exact separation vector *h*. Therefore, lag intervals are employed with the possibility of also using lag tolerances. Once the cross-variogram is standardized, the cross-correlogram is simply $\hat{\rho}(h) = 1 - \hat{\gamma}_s(h)$.

2.3.2 The Theoretical Correlogram and Cross-Correlogram

Since the sample estimates of the correlogram are binned by lag intervals, the average lag value is attributed to the mean lag distance. If a dataset has many observations, the lag distance may be small thus creating a smooth curve. Commercial real estate return data, however, do not produce a smooth correlogram such that a correlation value can be determined at all distances. Since the model desired should enable a real estate investor to compute the correlation value for any possible separation vector, the experimental correlogram is fit with the appropriate theoretical correlogram.

The three typical theoretical correlograms are the spherical, exponential and Gaussian. The three models are similar in shape with differences as to how quickly the model reaches a plateau or *sill*. The distance at which the theoretical correlogram reaches the sill is termed the *range*. The spherical theoretical model has a finite range, while the exponential and Gaussian theoretical models asymptotically approach a limiting value. The spherical model is probably the most commonly used bounded theoretical correlogram. Its equation is

$$\gamma(h) = 1.5\frac{h}{a} - 0.5\left(\frac{h}{a}\right)^3, \text{ if } h \le a$$

where a is the range. If h is greater than the range, $\gamma(h) = 1$. It has a linear behavior at small separation distance and reaches the sill at a. The tangent at the origin reaches the sill at about $2/3$ of the range.

Another commonly bounded theoretical model is the Gaussian. Its equation is

$$\gamma(h) = 1 - \exp\left(\frac{-3h^2}{a^2}\right),$$

where again a is the range. Unlike the spherical model, the Gaussian reaches its sill asymptotically thus the parameter a is defined as the practical range at which the correlogram is 95 percent of the sill. The distinguishing feature of the Gaussian model is its parabolic behavior near the origin.

After computing the empirical correlogram and cross-correlogram models, it is necessary, then, to decide on a theoretical model. While there are methods of fitting correlogram models, such as least squares and maximum likelihood as described by Cressie (1993), these techniques are not usually applicable for data resulting in a small number of correlogram points. Instead, a visual fit of the correlogram points to a few standard models is often satisfactory. Even when there are sufficient correlogram points, a visual check against a fitted theoretical model is appropriate as suggested by Hohn (1988).

Analysis shows that residential real estate results can be adequately modeled though a visual check. As a doubled check of the findings of this study I employed an Indicative Goodness of Fit (IGF) from Pannatier (1996) on the commercial property data to ensure the best theoretical variogram. The IGF is a number without units, which is standardized to compare across diverse experimental correlogram. An IGF value close to zero indicates a good fit. The IGF calculation is

$$IGF = \left(\frac{1}{N} \sum_{k=1}^{N} \sum_{i=0}^{n(k)} \frac{P(i)}{\sum_{j=0}^{n(k)} P(j)} \right) \left(\frac{D(k)}{d(i)} \right) \left(\frac{\gamma(i) - \hat{\gamma}(i)}{\sigma^2} \right)^2,$$

where

N = the number of directional variograms,
$n(k)$ = the number of lags relative to variogram k,
$D(k)$ = the maximum distance relative to variogram k,
$P(i)$ = the number of pairs for lag i of variogram k,
$d(i)$ = the mean pair distance for lag i of variogram k,
$\gamma(i)$ = the experimental measure of spatial continuity for lag i,
$\hat{\gamma}(i)$ = the modeled measure of spatial continuity for $d(i)$, and
σ^2 = the variance of the data for the variogram.

2.4 Commercial Property Results

In this section, I examine commercial real estate attributes using the empirical and theoretical correlogram. I use two commercial property attributes -- returns and capitalization (cap) rates. My first data source is the National Council of Real Estate Investment Fiduciaries (NCREIF) database, which collects quarterly prices for apartment, industrial, office, and retail properties. NCREIF data allow for testing within a submarket at the zip code level. I also create the correlogram for a database of apartment complexes given by Real Capital Analytics, Inc. Each observation is the sale of a multifamily unit. Neither dataset includes observations from Alaska and Hawaii due to the spatial discontinuity with the rest of the sample.

2.4.1 Spatial Correlation of NCREIF Base Returns

My initial focus is on measuring spatial correlation in a real estate sample, hence, I initially control for time series impacts using NCREIF returns from the second quarter of 2002 to the first quarter of 2003. While the NCREIF dataset contains observations from 1978, there are few consecutive quarterly returns that extend over a long time period. Thus, the sample that generates the most sample observations with the ability to examine spatial correlation totals 144 observations.

The 144 observations produce 10,296 unique pairs. I compute correlations for each of these pairs and contrast them against the distances of separation. Since the separation distances of real estate data are not uniform, I group sample pairs in bins. I find that the result using the NCREIF data exhibit a degree of variability with respect to size of the bin. To eliminate some of the arbitrary judgment of how large to establish the lag, and ensure each bin contains enough correlation pairs, the NCREIF findings use a 50 percent lag tolerance. Table 1 and Figure 2 present the empirical spatial correlations.

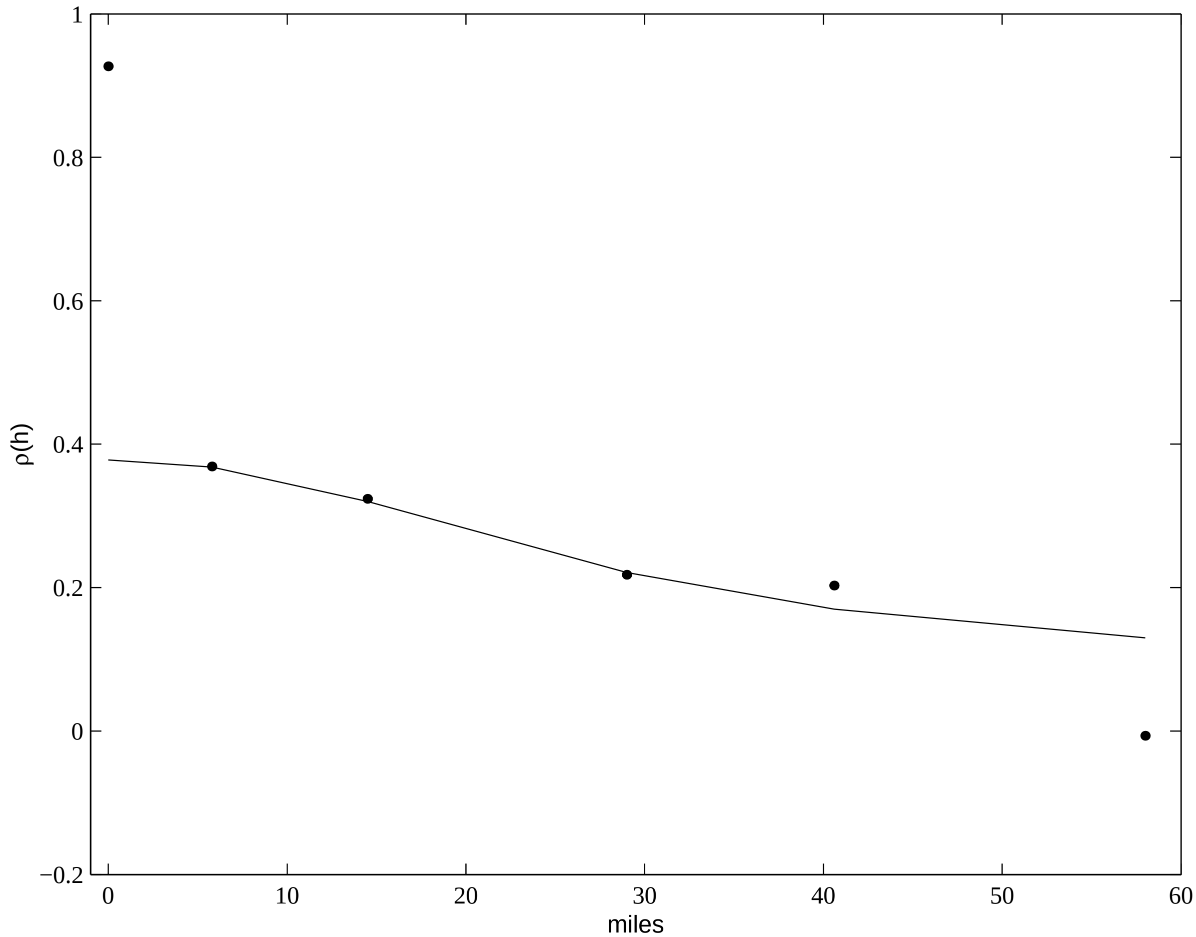

Figure 2: Spatial correlogram of U.S. commercial property returns.

Table 1: Spatial correlations in NCREIF base returns

Separation Distance	Number of Obs.	Experimental Correlogram	Theoretical Correlogram
0.0 miles	310	0.93	0.33
5.8 miles	114	0.37	0.21
14.5 miles	368	0.32	0.07
29.0 miles	310	0.22	0.00
40.6 miles	168	0.21	0.00
58.0 miles	94	-0.01	0.00
Log-likelihood			306.18

A significant feature of the NCREIF data is that multiple property exist within the same or adjacent zip code. In these instances, the separation distance, theoretically, equals zero. For the

NCREIF sample, 310 pairs are adjacent to each other. The associated spatial correlation for these 310 pairs is a near-perfect factor of 0.93.

The second separation distance demonstrates a spatial correlation of 0.37 at a distance of 5.8 miles. Subsequent correlations reduce monotonically to approximately 0.20 for a separation distance of 40.6 miles. After this distance the experimental correlogram value decreases to random spatial correlation. The last row in Table 1 indicates the separate distance where the spatial correlation between all commercial properties decays to zero is approximately 60 miles. After 60 miles, the empirical correlogram values become divergent.

2.4.2 NCREIF Returns Model

I recognize that there exist economic variables that explain correlations in commercial real estate returns that are not attributable to space. Thus, I next control for potential determinants of commercial property returns using an OLS specification, and subsequently model the residuals across separation distance. The OLS model controls for property type as well as proxies for property size and quality. Previous literature finds that economically based diversification may be preferable to purely geographic diversification. Wurtzebach (1988) removes geography boundaries and classifies cities based upon their dominant industry employment type and employment growth patterns. Subsequently, Mueller and Ziering (1992) test Wutzebach's diversification strategy and find that economic diversification offers an improvement over geographic regions such as state boundaries. Mueller (1993) also finds that a diversification strategy based upon nine SIC code categories provides superior diversification capabilities for a large real estate portfolio. Thus, I incorporate the economic variables detailed by Mueller (1993) and Cheng and Black (1998) in the following model.

$$R_{i,t} = \beta_0 + \beta_1 \bullet \ln(AVESQFT) + \beta_2 \bullet \ln(NUMUNITS) + \beta_3 \bullet \ln(MVLAST)$$

$$+ \beta_4 \bullet (APT) + \beta_5 \bullet (IND) + \beta_6 \bullet (OFFICE) + \beta_7 \bullet (RETAIL) + \beta_8 \bullet (POP)$$

$$+\beta_9 \bullet (EMPLOY) + \beta_{10} \bullet (RATIO) + \beta_{11} \bullet (MIG) + \varepsilon_{i,t}$$

where

$R_{i,t}$	=	the rate of return on the *i*th property for the *t*th quarter,
AVESQFT	=	average square feet,
NUMUNITS	=	average number of units, which is used by some apartment complexes instead of the *avesqft* measure
MVLAST	=	average market value from *t-1* quarter,
APT	=	dichotomous variable equal to 1 if the property is an apartment complex, and 0 otherwise,
IND	=	dichotomous variable equal to 1 if the property is an industrial building, and 0 otherwise,
OFFICE	=	dichotomous variable equal to 1 if the property is an office building, and 0 otherwise,
RETAIL	=	dichotomous variable equal to 1 if the property is a retail building, and 0 otherwise,
POP	=	population by age group,
EMPLOY	=	employment by industry,
RATIO	=	ratio of average house price over median household income, and
MIG	=	migration of persons into a zip code.

2.4.3 Spatial Correlation of NCREIF Residual Returns

Table 2 details the coefficients of the OLS parameters. The dependent variable is returns on commercial property. The data are concentrated within U.S. zip codes. *T*-statistics are in parentheses.

Table 2: Regression models to explain commercial property returns.

	Model					
Variable	A	B	C	D	E	F
Average Mkt. Value Last Quarter	1.84 (2.37)	1.88 (2.45)		2.07 (2.68)	2.06 (2.69)	
Average Square Feet	0.15 (0.41)		0.27 (0.73)	-0.03 (-0.09)		
Average Number of Units	1.22 (1.66)	1.13 (1.62)	1.52 (2.07)			
Apartment	-35.00 (-2.44)	-33.90 (-2.42)	-3.97 (-0.68)	-31.88 (-2.23)	-32.07 (-2.28)	5.58 (3.25)

table continued

Industrial	-29.34	-28.30	2.57	-31.23	-31.49	5.94
	(-2.06)	(-2.02)	(0.55)	(-2.18)	(-2.26)	(6.57)
Office	-36.86	-35.87	-3.03	-38.98	-39.24	0.32
	(-2.45)	(-2.43)	(-0.65)	(-2.59)	(-2.67)	(0.34)
Retail	-27.03	-26.01	6.52	-29.09	-29.35	9.93
	(-1.64)	(-1.60)	(0.76)	(-1.76)	(-1.81)	(1.36)
Adjusted R^2	0.15	0.16	0.13	0.14	0.15	0.11

Using the hedonic specification that has the greatest explanatory power as measured by adjusted R^2, I recalculate the correlogram with residual returns. The findings in Table 3 exhibit a reduction of correlations with the exception of the juxtaposed properties. Whereas the base returns exhibit an expected near-perfect spatial correlation, the residual returns exhibit a factor of almost equal value - 0.90. It would be improbable to economically diversify properties in adjacent zip codes, however, the data demonstrate that diversification by property type does not significantly reduce spatial correlation of commercial property in the same or adjacent zip codes.

Table 3: Spatial correlations in NCREIF residual returns

Separation Distance	Number of Obs.	Experimental Correlogram	Theoretical Correlogram
0.0 miles	300	0.90	0.29
6.0 miles	132	0.20	0.16
18.0 miles	434	0.21	0.00
32.0 miles	310	0.16	0.00
48.0 miles	90	0.04	0.00
Log-likelihood			318.76

The greatest reduction in spatial correlation is found for properties that are approximately 6.0 miles apart. The correlation decreases from a correlation of 0.37 to 0.20 for the residual returns. The correlation of the residual returns at this distance is comparable to the finding for base returns between 29.0 and 40.6 miles. Hence, it appears that diversification by property characteristics yields the greatest benefit for commercial properties in different neighborhoods, assuming a neighborhood does not extend greater than 6.0 miles.

Overall, the residual return findings demonstrate that economic and property-attribute diversification is somewhat effective in reducing spatial correlation and that the rate of decay is higher for heterogeneous property. Additionally, the distance to obtain random spatial correlation reduces from approximately 60 miles to about 50 miles.

2.4.4 Apartment Sales and Cap Rates

The correlograms to this point are based upon the NCREIF dataset. While the NCREIF data allow for examination of diversification across multiple property types, a criticism of NCREIF is that the values are based on appraisals. The use of appraisals is a potential problem because empirical evidence suggests that appraisals smooth changes in property values, which causes downward-biased estimates of total return volatility (Geltner (1991)). To protect against the specific panel of data driving the results, I compute the correlograms based on sales of apartment complexes from January 2001 to December 2003. Since the dataset includes returns and cap rates, I compute correlation models using both attributes.[1]

The experimental correlogram computations in Table 4, Panel A are base returns and comparable to the base NCREIF returns in Table 1. Whereas the base NCREIF returns decay to zero at approximately 60 miles, the first lag distance with adequate observations using the apartment sales is 96 miles. The spatial correlation at this separation distance is 0.28. At the further separation distance of 129 miles the spatial correlation is 0.11. Ultimately, the base apartment sales correlations decay to zero at approximately 144 miles.

[1] I also compute betas using an equally-weighted portfolio from this dataset. In general, the betas decay to zero at approximately 66 miles and a distance of 24 miles demonstrates spatial correlation of 0.23, but the number of observations is quite low.

Following the same method as the NCREIF returns, I compute spatial correlation values for residual returns after controlling for apartment property characteristics. The residuals in Panel B of Table 4 produce the same persistence in correlation as the base returns. The apartments exhibit spatial correlation of 0.11 at a distance of 96 miles after controlling for size and quality. This value compares to the NCREIF residuals which exhibit a correlation factor of the same magnitude (i.e., 0.15) at 41 miles and zero correlation by approximately 50 miles.

Table 4: Spatial correlations in apartment sales

Separation Distance	Number of Obs.	Experimental Correlogram
Panel A: Base Returns		
0.0 miles	140	1.00
96.0 miles	22	0.28
129.0 miles	36	0.11
144.0 miles	44	0.06
Panel B: Residual Returns		
0.0 miles	138	1.00
96.0 miles	22	0.11
129.0 miles	36	0.01

The results demonstrate stronger persistence in correlation across space than the NCREIF data. This may be due, in part, to the more geographically continuous nature of multifamily housing, a heavy concentration of properties in Florida, Texas, and California, and/or the lack of diversification by property type. Another explanation could be a low number of data pairs at shorter separation distances. The spatial literature recommends at least 30 pairs per lag distance, which is not the case at the second lag distance using apartment sales.

To assuage small sample concerns, I also compute spatial correlograms using 1,520 apartment cap rates, which results in 2 million correlations. The spatial correlations of base cap rates detailed in Table 5 follow a pattern comparable to the base NCREIF commercial returns.

The initial spatial correlation of juxtaposed apartment complexes demonstrates an almost perfect relation. Further, the distance of random correlation is again approximately 60 miles.

Table 5: Spatial correlation in base apartment capitalization rates

Separation Distance	Number of Obs.	Experimental Correlogram	Theoretical Correlogram
0.0 miles	3,104	0.99	0.44
1.5 miles	1,196	0.42	0.39
3.0 miles	4,362	0.33	0.35
6.0 miles	6,272	0.26	0.31
12.0 miles	6,268	0.21	0.25
24.0 miles	5,270	0.24	0.16
30.0 miles	5,126	0.20	0.13
36.0 miles	4,776	0.15	0.10
45.0 miles	4,120	0.14	0.07
51.0 miles	3,372	0.09	0.06
60.0 miles	6,268	0.04	0.03

Similar to the NCREIF and apartment returns, I execute an OLS regression on the apartment cap rates, controlling for number of units, age, and a proxy for size and quality. The residual correlations in Table 5 are similar in magnitude to the NCREIF residual returns. Again, the results demonstrate a correlation of 0.21 at 6.0 miles, which reinforces the strategy of purchasing real estate properties in different submarkets. The point of random correlation is found at approximately 72 miles.

Table 6: Spatial correlation in residual apartment capitalization rates

Separation Distance	Number of Obs.	Experimental Correlogram	Theoretical Correlogram
0.0 miles	2,906	0.99	0.40
6.0 miles	78	0.21	0.29
18.0 miles	332	0.13	0.21
36.0 miles	378	0.17	0.15
54.0 miles	464	0.11	0.11
72.0 miles	532	0.02	0.08

2.4.5 MSA Pairs

Thus far, the empirical commercial results from multiple datasets using two property attributes produce i) near-perfect initial spatial correlations, even after diversifying by property characteristics and economic determinants, ii) a reasonably monotonic reduction in correlations as separation distance increases, and iii) comparable distances of random spatial correlation. Our next test examines the return correlation of MSA pairs that are adjacent to one another. I examine these specific MSA pairs to ensure spatial discontinuity is not driving the empirical results. For example, there are no return data for commercial properties in the expansive rural areas of western U.S. Since commercial properties cluster in metropolitan areas, I examine 52 MSA pairs in which the metropolitan area is continuous and no rural land exists between the paired observations.

I use NCREIF data to compute sub-MSA quarterly returns, augmented with economic data. The economic data consists of annual employment growth rates for the entire sub-MSA and within five major industry classifications, and population growth rates of five age groups. In addition to providing sub-MSA observations, the NCREIF data offer the benefit of a longer time series. Of the MSA pairs that exhibit statistical significance, the shortest time series is 16 quarters and the longest is 92 quarters. Since I want to focus specifically on the spatial aspects of commercial real estate portfolios, I control for time-series aspects using the NCREIF national property index, and model the residuals after controlling for the national index and economic data.

For the entire sample of 52 MSA pairs, the separation distance measures from 3.67 miles to 111.25 miles. The empirical results from previous tests suggest that the separation distance for random spatial correlation is approximately 50 to 60 miles. Of the sample of 52, twelve pairs exceed 60 miles in separation distance. Five of the twelve pairs possess statistically significant correlations before controlling across the time series. After I control for the national property index, economic variables, and property characteristics, I find that none of the twelve with separation distances over 60 miles are significant. This result is consistent with previous findings.

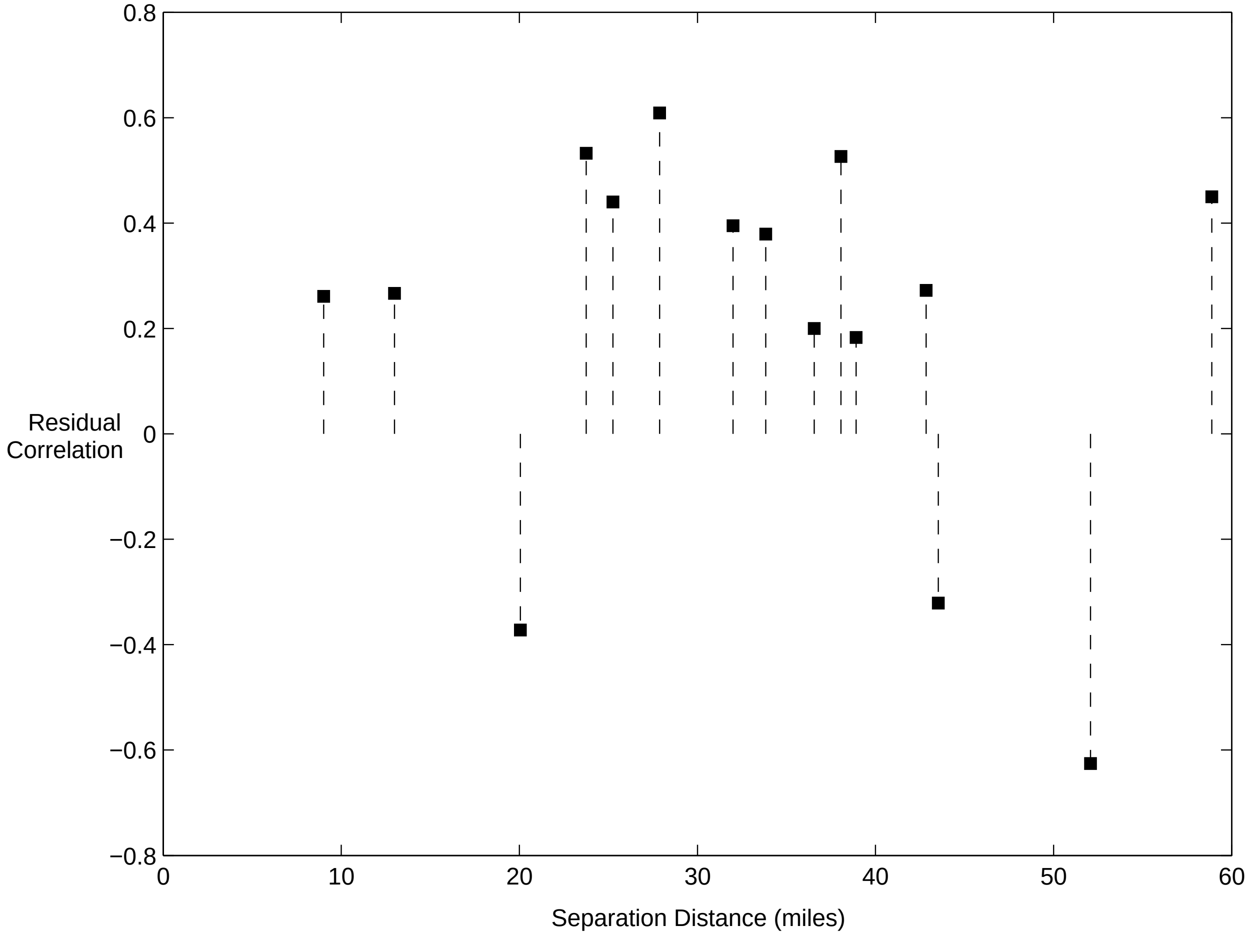

Figure 3: Spatial correlation in CMSA pairs.

After controlling for the national property index and other variables, many of the 52 sub-MSA pairs are not statistically significant. Figure 3 displays the MSA pairs that demonstrate residual return correlations that are significant. Of the fifteen significant pairs, twelve exhibit positive correlation. The correlation findings of the shortest two separation distances (9.02 and 12.99 miles) are consistent with previous results. The correlations of approximately 0.25 are similar to the NCREIF residual returns and apartment residual cap rates at the same distances. Somewhat surprising is the cluster of positive correlations between separation distances of 24 to 43 miles. The average distance is 33.23 miles with an average correlation within this cluster of 0.39. This result suggests that spatial correlation exists within MSAs.

2.5 Residential Property

In addition to multiple databases and two different real estate attributes, I also want to examine the impact of residential property on the spatial aspect of commercial property. While most commercial real estate investment portfolios will not incorporate residential property, local housing markets can offer insight into the economic behavior of commercial property. I examine base and residual residential returns and then combine commercial and residential data types in the next section.

I compute residential returns from the Neighborhood Change Database (NCDB), a dataset that geographically standardizes the U.S. decennial census based upon year 2000 census tracts. I compute 9000 base residential returns initially aggregated to the zip code level. The resulting correlogram models use over forty million pairs. I also compute returns over the various decade combinations of 1970 to 1980, 1980 to 1990, and 1970 to 1990. Table 7 shows the values of the base returns.

Table 7: Spatial correlations of residential base returns.

Separation Distance	Number of Obs.	Experimental Correlogram	Theoretical Correlogram
Panel A: 1970-1980			
30.61 miles	345,901	0.38	0.42
153.05 miles	513,825	0.28	0.36
306.10 miles	709,321	0.20	0.28
459.15 miles	832,363	0.24	0.21

table continued

612.20 miles	816,794	0.19	0.14
765.25 miles	670,650	0.10	0.08
948.91 miles	671,954	0.00	0.01
Panel B: 1980-1990			
15.31 miles	130,541	0.57	0.62
61.22 miles	219,652	0.54	0.51
122.44 miles	239,948	0.42	0.38
183.66 miles	274,317	0.37	0.25
244.88 miles	332,306	0.20	0.14
275.49 miles	338,173	0.13	0.09
306.10 miles	360,056	0.01	0.04
Panel C: 1970-1990			
30.61 miles	345,901	0.35	0.40
153.05 miles	513,825	0.35	0.33
306.10 miles	709,321	0.19	0.26
459.15 miles	832,363	0.14	0.19
612.20 miles	816,794	0.12	0.12
765.25 miles	670,650	0.09	0.07
918.30 miles	652,836	0.06	0.02
1,010.13 miles	722,171	0.01	0.00

The results indicate a significantly lower initial spatial correlation than commercial property. This is due, in part, to a lack of return values where the separation distance is theoretically zero. Therefore, the initial spatial correlation measures 30.61 miles in a separation distance. The resulting spatial correlation is 0.35. Subsequent correlation decays monotonically to a zero separation distance at 1,101.13 miles, a considerably longer distance than the commercial property results.

Similar to commercial returns, it is reasonable to expect that there exist determinants that explain a portion of the correlation. Thus, I regress the base residential returns by some typical determinants of housing prices, such as education, family income, a proxy for house size, the number of persons of age to buy a home, and the age of the home. Table 8 presents the coefficients and *t*-statistics of the regression model of 1970-1980 residential returns. As expected, all determinants are statistically significant at the 5 percent level. The specification is

$$R_{i,t} = \beta_0 + \beta_1 \bullet \ln(EDUC12) + \beta_2 \bullet \ln(EDUC16) + \beta_3 \bullet \ln(EDUCPP) + \beta_4 \bullet \ln(INCOME)$$

$$+ \beta_5 \bullet \ln(SIZE) + \beta_6 \bullet \ln(BLTOC70) + \beta_7 \bullet \ln(BLTOC59) + \beta_8 \bullet \ln(BLTOC49)$$

$$+ \beta_9 \bullet \ln(BLTOC39) + \varepsilon_{i,t}$$

where

R_i	=	the rate of return on the *i*th house,
EDUC12	=	persons 25 years old or older who completed high school,
EDUC12	=	persons 25 years old or older who completed college,
EDUCPP	=	number of persons 25 years and older,
INCOME	=	average family income,
SIZE	=	aggregate number of rooms in a home, and
BLTOC	=	total occupied housing units built up to the year specified in the variable.

Using the OLS residuals, I compute the return correlations for each observation within census tracts. The residuals are not aggregated across zip codes but left within census tracts since each observation is the remaining portion not explained by the model, and thus is unique information. This method produces slightly less than one billion observations for each time period. Table 9 provides the details for the longer period from 1970 to 1990.

Table 8: Hedonic regression model of 1970-1980 residential returns.

	Log. Return using 1970 RHS variables	Log. Return using 1980 RHS variables
Intercept	5.925 (46.97)	-1.373 (-10.44)
High School Education (*educ12*)	0.094 (9.90)	0.126 (13.70)
College Education (*educ16*)	0.045 (10.76)	0.038 (7.70)
Num. of Persons 25 yrs. & older	-0.579 (-26.84)	-0.020 (-0.92)

table continued

Family Income (*income*)	-0.021 (-1.73)	0.365 (31.22)
Aggregate Number of Rooms (*size*)	-0.169 (-8.60)	-0.099 (-5.27)
Year built 1970-1980 (*bltoc80*)		0.167 (93.68)
Year built 1960-1969 (*bltoc70*)	0.080 (44.01)	-0.070 (-21.67)
Year built 1950-1959 (*bltoc59*)	0.023 (7.12)	-0.152 (-41.03)
Year built 1940-1949 (*bltoc49*)	0.009 (2.61)	0.011 (3.00)
Year built 1970-1980 (*bltoc39*)	0.004 (1.51)	-0.079 (-33.09)
R^2	0.4996	0.4667

Table 9: Spatial correlations of residential return residuals.

Separation Distance	Number of Obs.	Experimental Correlogram	Theoretical Correlogram
Panel A: 1970-1980 using 1970 RHS variables			
15.31 miles	4,777,264	0.14	0.15
30.61 miles	6,192,038	0.13	0.15
76.53 miles	4,175,299	0.13	0.13
153.05 miles	4,883,237	0.09	0.09
229.58 miles	5,898,320	0.08	0.04
306.10 miles	6,478,281	0.04	-0.01
Panel B: 1980-1990 using 1990 RHS variables			
30.61 miles	7,156,825	0.13	0.20
61.22 miles	5,528,380	0.20	0.19
153.05 miles	6,429,092	0.22	0.13
229.58 miles	7,637,638	0.22	0.07
244.88 miles	8,104,028	0.11	0.06
260.19 miles	9,058,917	-0.03	0.05
Panel C: 1970-1990 using 1990 RHS variables			
15.31 miles	4,783,788	0.19	0.25

table continued

30.61 miles	6,198,538	0.17	0.25
76.53 miles	4,178,956	0.22	0.23
153.05 miles	5,898,176	0.22	0.19
229.58 miles	6,483,273	0.07	0.08
382.63 miles	7,302,486	0.09	0.03
428.54 miles	7,112,267	0.03	0.01

While the magnitude of the spatial correlations is not surprising, it is interesting to note that, based on millions of observations, residential properties extending 150 - 225 miles in separation distance demonstrate an empirical correlation of roughly 0.20. One implication is that public policy changes and economic conditions in one community could have substantial spillover effects on property values in communities hundreds of miles away.

2.6 Combining Commercial and Residential Types

Given the voluminous amount of data available for residential property, I next examine the effect of including the residential property type in the commercial analysis. Inclusion in the correlogram is based upon the fact that commercial and residential markets are affected by similar economic conditions at common locations. Another argument is termed co-kriging in the spatial literature. The reasoning follows that if the secondary residential returns are correlated with the primary commercial returns, then one can utilize observations at sites where they are both recorded to estimate this correlation. Hence, I use the residential returns as an independent variable in the previous NCREIF commercial return specification. I also use another spatial econometric model to determine if the two general types of property returns have a common spatial correlation.

2.6.1 Commercial Correlogram with Residential Returns

To discover how residential returns can offer additional insight into commercial spatial correlation, I match residential returns by location and include them as an explanatory variable in the NCREIF commercial return specification along with the other property characteristics. I lag the residential returns one quarter to avoid potential simultaneity between commercial and residential prices in the same quarter. The other change of the NCREIF specification is that the economic variables are removed since residential real estate is a proxy for economic conditions at common locations.

The spatial correlation results in Table 10 are consistent with previous findings. The empirical results indicate a separation distance to obtain random spatial correlation between 40.6 and 58 miles. Also consistent with previous results is the high initial correlation of adjacent properties. The correlation value of 0.89 is effectively the same as the factor using NCREIF residuals.

Table 10: Spatial correlations in commercial residuals after controlling for residential returns.

Separation Distance	Number of Obs.	Experimental Correlogram	Theoretical Correlogram
0.0 miles	308	0.89	0.30
5.8 miles	114	0.30	0.28
14.5 miles	364	0.12	0.19
29.0 miles	308	0.07	0.02
40.6 miles	168	0.12	-0.03
58.0 miles	92	-0.11	-0.05

2.6.2 Cross-Correlogram

Spatial econometrics offers a specification termed the cross-correlogram, whereby two data types can be combined into the same model. The cross-correlogram combines the correlation of two commercial properties with the correlation of two residential properties. I compute cross-spatial correlations using commercial and residential returns for each unique location.

Since the NCDB data are not available for the NCREIF quarters under study, I use residential data from the Office of Federal Housing Enterprise Oversight (OFHEO). The OFHEO dataset provides quarter residential housing prices, which I match to the 144 zip code observations from the NCREIF data. Table 11 reports the findings of matching the commercial and residential property returns. It appears that the cross-correlogram combines the findings of both the residential and commercial data. First, the initial correlation is not as pronounced as the commercial correlograms but slightly more than the residential models. Second, the distance of random spatial correlation increases, which could be the residential influence of residual correlation at hundreds of miles. Last, the rate of decay appears to be a compromise between commercial and residential property types. The cross-correlogram values compute between 0.50 and 0.37 from zero separation distance to 87 miles. After 87.0 miles the correlation decays immediately to zero at 101.5 miles.

Table 11: Cross-correlogram values of commercial and residential returns.

Separation Distance	Number of Obs.	Experimental Correlogram	Theoretical Correlogram
0.0 miles	136	0.50	0.50
14.5 miles	368	0.50	0.48
29.0 miles	312	0.41	0.42
43.5 miles	166	0.38	0.33
58.0 miles	94	0.37	0.24
72.5 miles	44	0.42	0.15
87.0 miles	20	0.41	0.08
101.5 miles	50	-0.02	0.03

2.7 Applying Empirical Results to Portfolio Theory

From the various empirical insights of the spatial correlation of commercial real estate, our last analysis is to apply the empirical findings to the theoretical understanding from section 2. Equation (1) shows that, asymptotically, the risk of a real estate portfolio is the average correlation. I apply this result to three simulations to determine real estate portfolio risk.

At one end of the spectrum is the situation when a real estate portfolio manager desires to directly own properties within adjacent zip codes or a sub-market. Given that the spatial correlation of such a portfolio is approximately 0.90, a question arises as to how many properties should this investor own to reduce the unsystematic risk. This is akin to building a diversified stock portfolio where the benefits of diversification are achieved with approximately fifteen less-then-perfectly correlated stocks.[2] The theory in section 2 shows that, asymptotically, the average correlation will be realized for a portfolio. For a finite number of real estate assets the spatial correlation will not only be the correlations between the assets but the variance of each real estate property (the diagonal of the variance-covariance matrix). The correlation of an asset with itself is one, thus, the risk of a portfolio concentrated in a sub-market or adjacent zip codes is at least 0.90, without regard for the number of properties.

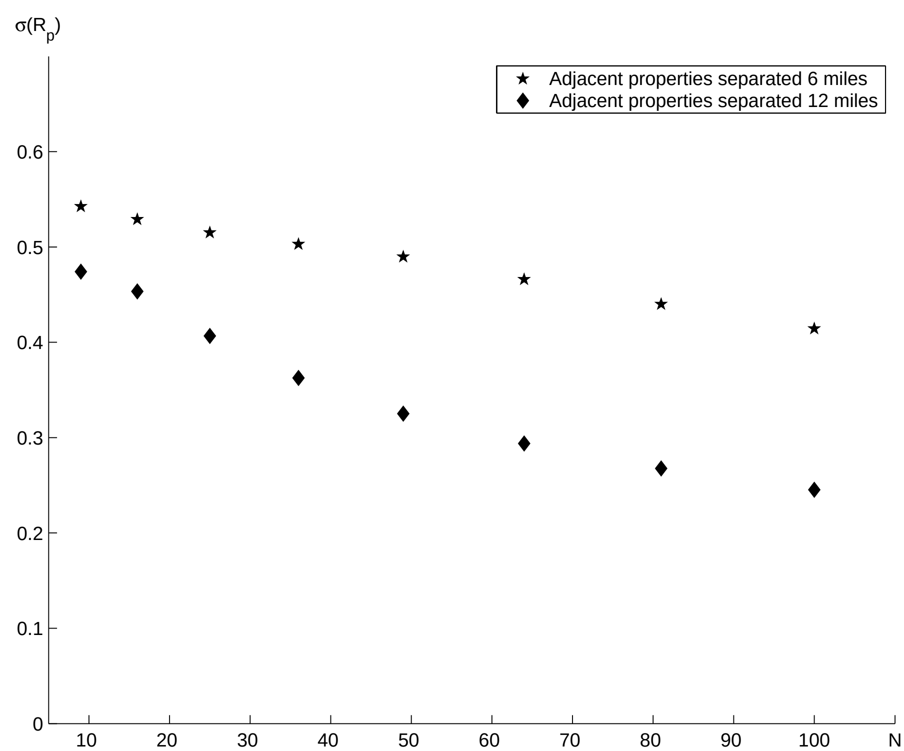

Figure 5: Real estate portfolio risk as a function of spatial correlation.

[2] Fama (1976) finds the portfolio standard deviation of an equally weighted portfolio of two securities is 7.2 percent, which reduces monotonically to 3.8 percent with a portfolio of fifteen randomly selected stocks

On the other end of the spectrum is the scenario when a commercial property portfolio holds property at least 60 miles in separation distance, including owning property of the same type. Using Consolidated MSAs centroids as defined by the U.S. Census Bureau, I note that there are no CMSAs within the largest 50, as measured by population, that are within 60 miles of any of the other largest 50 CMSAs. Further, 4,946 out of the 4,950 pairs of the largest 100 CMSAs are at least 48 miles apart and 11,164 out of the 11,175 pairs of the largest 150 CMSAs are separated by at least 48 miles. Overall, there exist 36,267 pairs of the 270 contiguous U.S. CMSAs that result in a separation distance equal or greater than 60 miles. Hence, a strategy to remove spatial risk from a real estate portfolio is to hold one property per MSA. Holding one property in each of the 50 largest MSAs will reduce the portfolio standard deviation to $1/\sqrt{50}$ or 14 percent.

Given the search and on-going portfolio costs associated with owning one property per MSAs, I next consider owning properties within the same MSA submarket but in diverse neighborhoods. Note that the largest rate of decay in spatial correlation occurs beyond juxtaposed properties. Therefore, I conduct simulations of portfolios using a square grid of properties where the adjacent properties are six or twelve miles apart. The resulting portfolio standard deviations are presented in Figure 5. Assuming a six mile separation distance between adjacent properties, the leftmost star in Figure 5 indicates a portfolio standard deviation of 54.2 percent for a 3x3 square grid of nine properties. Adding more properties to the portfolio helps reduce the spatial correlation. The portfolio standard deviation is 52.9 percent for a 4x4 grid of 16 properties, 50.3 percent for a 6x6 configuration, and 46.6 percent for 64 properties. While the spatial correlation decays monotonically, a total of 100 properties produce significant unsystematic portfolio risk of 41.4 percent.

The results of the simulation assuming twelve mile separation distance between neighboring properties are better with regards to reducing spatial correlation but may not be entirely practical.

The findings in Figure 5 show that the portfolio standard deviation begins at 47.4 percent for nine properties in a 3x3 square grid. Again, the spatial correlation decays as more properties are added to the portfolio such that a 10x10 grid of 100 properties results in a portfolio standard deviation of 24.5 percent. While the spatial correlation is reduced, the practical question becomes one asking how many properties can be owned within an MSA submarket. The geometry of the portfolio is important since properties owned in a straight line will yield a lower spatial correlation. However, most MSA submarkets will be limited to five or six properties in a straight line at twelve miles apart. Additional properties will increase overall spatial correlation because any new property cannot be extended along the straight line but, instead, added next to an existing property. This fact, termed infill in the spatial literature, generates an increasingly denser spatial portfolio. And even if a real estate portfolio manager owned, for example, seven properties in a straight line from one end to the other, the portfolio standard deviation equals roughly 40 percent.

Since the proceeding three simulations are based upon the same property type, I also examine the impact of diversification by property type. Because the two extreme scenarios of no spatial diversification and total spatial diversification do not change, I examine the effects of property-type diversification within an MSA submarket. The results demonstrate that diversification by property type does not mitigate portfolio risk. For example, a portfolio of 16 properties diversified using the four main property types and each separated by at least 18 miles, produces portfolio standard deviation of 27 percent. I look at the other combinations of 25 properties in a 5x5 grid with adjacent properties separated by at least 12 miles, 36 properties in a 6x6 grid separated by at least 15 miles, and 60 properties in a 6x10 grid separated by at least 15 miles. The portfolio standard deviations are 32 percent, 24 percent, and 19 percent, respectively.

These simulations demonstrate that spatial correlation in real estate portfolios is significantly different than the traditional finance models where unsystematic risk is quickly reduced as more stocks are added to a portfolio. In fact, adding more properties to a real estate portfolio may increase unsystematic risk due to infill.

2.8 Chapter Summary

Real estate is a field built on the notion of location, yet the commercial real estate portfolio the literature does not formal spatial techniques to examine the effects of geography on commercial property portfolios. Consistent with the axiomatic importance of location on commercial property prices, this chapter employs spatial econometrics to quantify the spatial correlation of commercial property. Adoption of the methods will assist portfolio managers in creating efficient commercial real estate portfolio.

The next chapter addresses another large-scale real estate portfolio. REITs are a popular investment vehicle, particularly for those investors who self select to received dividend income. The next section investigates the dividend policy of REITs.

3. REIT Dividend Payouts

REITs are currently required by tax law to pay out 90 percent of its taxable earnings to maintain the REIT organizational form. Initially, this constraint appears binding, leaving a REIT manager with limited latitude to dictate payout policy. However, as detailed in Wang, Erickson, and Gau (1993) and Kallberg, Liu, and Srinivasan (2003), some REITs possess payout flexibility. Particularly for equity REITs, which directly own real estate assets, the 90 percent payout of taxable earnings can be significantly different from the gross cash flows.

The ability of REIT managers to vary dividend payouts has led to conflicting explanations in the real estate literature as to what REIT managers are accomplishing by managing their payout policies. On one hand, Wang, Erickson, and Gau (1993) explore the determinants of REIT dividend payouts, and find that, on average, REITs with lower return-on-asset ratios demonstrate higher dividend payouts. They contend that the market has less incentive to monitor a REIT with superior performance, therefore, REIT dividend policies are at least partially determined by agency cost theory. Lee and Slawson (2005) also find evidence of agency-cost explanations based upon the dividend policies of inefficiently monitored REITs. On the other hand, Bradley, Capozza, and Seguin (1998) examine REIT dividends as a function of cash flow uncertainty, and find that a fitted volatility measure is significantly negatively correlated with the payout of dividends. They posit that their findings are consistent with information-based theories and not agency-cost explanations.

I reexamine the dividend behavior of REITs to address the open issue, and find results that are materially different from the previous studies. Using explanatory variables based upon studies of dividend policy from the financial economic literature, I find that the dividend payment made by equity REIT managers are not affected by traditional measures of agency costs or asymmetric information. Instead, the results confirm the importance of contemporaneous net income and the level of dividends paid last period, which is direct affirmation of the Lintner (1956) partial adjustment model that is prevalent in the finance literature. The other two factors that have some statistical power in explaining REIT dividend payments are the natural logarithm of assets, which I argue is a proxy for firm volatility, and the tax law change effective January 2001, when the 95 percent payout of taxable earnings was reduced to 90 percent.

One of the reasons our results differ from previous studies is the understatement of standard errors that cloud inferences. Dividend payments are correlated cross-sectionally and across time. Also, dividend payments exhibit endogeneity with a number of the independent variables that explain dividend payouts. I account for these econometric issues using generalized least squares (GLS), two-way random effects, instrumental variables (IV), and by scaling appropriate variables by total assets. I find that proper econometric methods have a material effect on the results.

In addition to explaining dividend payments with a full model, I restrict the specification to the Lintner (1956) partial adjustment model, and examine whether REITs smooth their dividends. I note that REITs are not strict residual payers, however, the Lintner (1956) model does not detect much dividend smoothing. The raw data demonstrate some systematic dividend payments, but this is not detected by the Lintner (1956) model.

The remainder of the study proceeds as follows. Section 3.1 presents background on market imperfections and the REIT structure. Section 3.2 explains the sample and research design. Section 3.3 presents the empirical results. Section 3.4 summarizes the chapter.

3.1 The REIT Structure

REITs possess a straightforward organizational structure to examine dividend policy. This is especially true when compared to industrial firms. For non-REIT firms, project confidentiality, adverse selection, and moral hazard can hinder the direct transfer of information between market participants. Conversely, REIT investors and analysts are aware of the real estate assets and mortgages held by publicly traded REITs. In general, REITs are valued similarly to non-REIT firms -- investors discount future cash flows. Given (i) the ability to witness the holdings of a REIT, (ii) that there exists an active market for assets similar to those owned by REITs, and (iii) the REIT's income is not based upon technologically advanced processes, investors have greater insight into the future cash flows of a REIT. This is especially true for mortgage REITs where there is little, if any, private information regarding the balance sheet.

One of the conditions of REIT status is that at least 75 percent of a REIT's assets must consist of real estate assets, cash, and government securities. A further requirement is that at least 75 percent of the REIT's gross income must be obtained from real estate assets. These conditions aid in our examination of dividend policy by restricting firms in the study to the real estate industry and reducing industry effects. Further, Demsetz and Lehn (1985) argue that regulation restricts the investment options available to managers. Smith and Watts (1992) extend the argument by predicting that a restricted investment set assists in mitigating agency problems. It follows that disciplining mechanisms and management's impact on firm value are reduced in all types of REITs.

Jensen's (1986) free cash flow hypothesis has another implication for REITs. The free cash flow hypothesis of Jensen (1986) argues that agency costs are reduced and firm value is maximized when management adheres to a policy of paying out all FCF, which is the amount in excess of the funds required to fund positive net present value (NPV) projects. By dispensing all FCF, the amount of resources under the control of managers is reduced, thereby reducing managerial power and the potential of empire building. Since REITs must pay out 90 percent of their taxable income, it follows that a manager's discretion over FCF is reduced.[3] Consistent

[3] The payout percentage was 95 percent until December 31, 2000.

with the FCF hypothesis, Mooradian and Yang (2001) find that equity REITs within the hotel industry have significantly smaller amounts of FCF than non-REIT hotel firms.

By organizational form, REITs eliminate taxes from the examination of dividend policy. In addition, REITs control for tax clientele effects. Due to the required dividend payments and high yields, REITs creates a subset of dividend-paying stocks that should result in a homogenous investor clientele. Investors purchase REIT stocks knowing that they will receive a high dividend yield, and REIT shareholders self select based upon their preference for taxable income.

Equity REITs offer another reduction in asymmetric information when assessing firm value. Instead of discounting long-term dividend projection like non-REIT firms, REIT analysts estimate the aggregate net operating income of the REIT's holdings for the next year. The aggregate net operating income is then capitalized by a weighted average capitalization rate for the portfolio. The capitalization rates for REITs are quite specific and standardized within each particular REIT sub-industry (e.g., apartment, industrial, and retail). As detailed by Ling and Archer (2005), capitalization rates are determined directly from comparable sales transactions, appraisers, and institutional investors. The capitalization process also uses information from the private real estate market to perform a mass appraisal of the REIT's properties. The ability to use information from the well-functioning private real estate market to value shares of a publicly traded REIT is unique and distinguishes the REIT market from other industries where assets are not separately traded in a private market.

Thus far I have described an organizational form that possesses mechanisms that eliminate consideration of taxes and significantly reduce the effects of agency problems and asymmetric information. The other market imperfection described by Allen and Michaely (1995) that REITs control for is transaction costs. Because the REITs capital structure requires a 90 percent payout of taxable income, capital accumulation and FCF are reduced. It follows that agency costs and asymmetric information are reduced since REITs must continuously be active in the capital markets, and these markets act as an additional monitor of firm activities. And while REITs must expend effort on obtaining new capital, at the margin, the transaction costs associate with new capital is minimal since the firm is constantly in the market.

In general, REITs closely align with the perfect market assumptions of the MM (1961) dividend irrelevance theory. REITs also remove Black's (1976) dividend puzzle from consideration since REITs must pay a dividend and are not taxed if the firm meets qualification requirements. Many theoretical and empirical studies examine the interaction of these market imperfections with dividend policy, however, I are unaware of any studies that are able to control for the market inefficiencies in the manner of the REIT structure.

3.2 Dividend Payout Research Design

This study examines firms from the Compustat database with SIC code 6798 from 1992 to 2003. Prior to 1992, REITs operated on a deal-to-deal basis, and were opportunistic in looking for the cheapest financing deals each month. Also, they were largely entrepreneurial companies with little to no centralized support or corporate governance. The modern REIT has moved to a corporate finance mindset, relying more on setting long-term strategies to guide their decisions. Ott, Riddiough, and Yi (2005) find that financing policy stabilized during what they term the new-REIT period after 1992. They conjecture the stabilization is an outcome in response to monitoring by outside investors and rating agencies. Additionally, the year 1992 was when the Taubman Centers REIT developed the UPREIT, or Umbrella Partnership REIT, as a mechanism to enable property owners to defer recognition of capital gains on properties contributed to the REIT in exchange for partnership units. The UPREIT structure is common in today's REIT industry, hence, I control for the structure by beginning the study after its introduction.

From the sample of firms with SIC code 6798, I confirm each firm as either an equity or a mortgage REIT. I remove any hybrid REITs and other firms that are listed in Compustat with the SIC code 6798 but are not REITs. Hybrid REITs, which hold a balanced mix of debt obligations and real properties, are removed to study the dividend policy of the equity and mortgage REIT environments without clouding the inferences using an organizational form holding both types of assets. I also remove captive trusts since Hsieh and Sirmans (1991) find that REIT that are captive financing vehicles for their sponsors demonstrate financial performance different than non-captive REITs. Lastly, I remove liquidating trusts that are set up solely to dispose of the real estate assets.

One of the main issues in any empirical work regarding dividend payouts is the assumption of independent random error terms in a model to explain dividend payments. Dividend payers avoid reducing dividend payouts and, thus, tend to smooth dividend payments. The very definition of dividend smoothing implies serial correlation. Further, small (large) firms tend to pay smaller (larger) dividends, thus, heteroscedasticity is an issue. When cross-section regressions are employed in previous finance and real estate empirical studies, the correlation of residuals across firms seems to be ignored. When panel data is employed, both the cross-section and time series autocorrelation have not been corrected. Ordinary least squares (OLS) estimators, while unbiased, are inefficient in studies of dividend payments, which understates standard errors and clouds inferences. Hence, any inference may not correctly portray the true state of nature of dividend policy. I find that the residuals of an unrestricted model accounting for the economic explanations of dividend payout exhibit serial correlation with an estimated first order coefficient of 0.25. Durbin-Watson autocorrelation tests are statistically significant with *p*-values less than 0.01. I correct for the serial correlation of dividend smoothing by employing generalized least squares (GLS), using the OLS residuals to estimate the covariances across observations (i.e., Yule-Walker estimates). Also, I correct for heteroscedasticity by scaling the dividend payments by total book assets.

3.3 Dividend Payout Empirical Results

An initial examination of dividend payouts of U.S. equity and mortgage REITs reveals that REITs pay out considerably more than non-REIT firms. Figure 6 illustrates the mean and median payout of preferred and common stock dividends, combined, as a percentage of net income for REITs, as well as mean payout of a 40 percent sample of non-REIT firms from the Computstat Industrial database. The REIT measures include mortgage and equity REITs but no hybrid structures. As shown, REITs pay out considerably more dividends than non-REIT firm. Further, the median REIT payout in most years is higher than 90 percent payout required by REIT tax law. In contrast, the average dividend payout for non-REIT firms is a reasonably stable 22 percent.

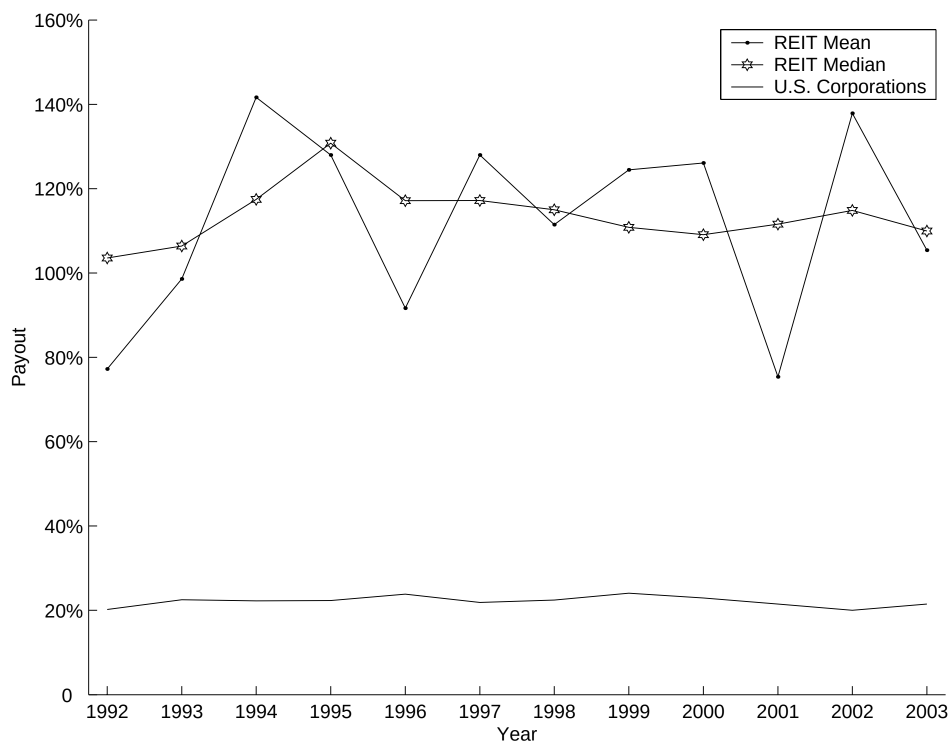

Figure 6: Dividend Payouts of REITs and Industrial Firms

3.3.1 Residual Payout Test

Due to the high dividend payout, one expectation is that REIT managers must follow a residual payout policy, which implies that REITs pay out all amounts left over after deducting capital expenditures from internally generated cash flows, and have little discretion over their dividend policy. To test this hypothesis, I use a measure of residual payout policy taken from Baker and Smith (2006), who standardize the amount of FCF by the contemporaneous market value for non-REIT firms. FCF is determined in the manner employed by Lehn and Poulsen (1989). The intuition of the measure is that if a firm follows a residual dividend policy, they will exhibit a mean, median, and standard deviation of standardized FCF near zero. The details of the measure for both REIT and non-REIT firms, and residual policy firms (RPFs) and non-RPFs are presented in Table 12.

Table 12: Statistical measures of REIT standardized free cash flow.

Statistical Measures	All REITs	Equity REITs	Mortgage REITs	B&S Non-REIT RPFs	B&S Non-REIT Non-RPFs
Mean	1.88	2.28	-2.13	1.46	23.62
Median	2.90	2.94	1.58	1.51	4.42
Standard Deviation	27.44	27.45	27.08	1.93	56.05

For the full sample of REITs from 1992 to 2003, the average standardized FCF is 1.88 percent and the median is 2.90 percent. Surprisingly, the standard deviation of the standardized measure is 27.44 percent. In comparison, the Baker and Smith (2006) study finds that the two quintiles exhibiting the metrics closest to zero, and considered to be RPFs, demonstrate an average standardized FCF of 1.46 percent, a median standardized FCF of 1.51 percent, and an average standard deviation of 1.93 percent. The firms in the Baker and Smith (2006) paper that are at the opposite end of the spectrum, and considered to be non-RPFs, exhibit an average standardized FCF of 23.62 percent, a median of 4.42 percent, and a standard deviation of 56.05 percent. Thus, the mean of standardized FCF for REITs is more in line with firms that follow a residual dividend policy, however, the median and standard deviation REIT metrics are not conclusive.

To determine if REIT type has an impact on whether a firm adheres to a residual dividend policy, I split the sample between equity and mortgage REITs and compute the standardized FCF metrics for each subsample. A rationale for this test is that equity REITs will have more FCF after the sale of a major holding and may not immediately invest the funds into another project. Holding onto the cash, and thus affecting the standardize FCF measure, until the opportune time can still fulfill the maximization of shareholders' wealth, but will not cause the equity REIT to distribute excess cash to shareholders. Alternatively, mortgage REITs may not have the ability to maintain FCF due to the lack of tax shields, or may not desire to hold on to cash in the same manner due to a continuous supply of investment options in the U.S. mortgage market.

The results of splitting the sample based upon REIT types are consistent with the full sample. I find that 1,469 firm-year equity REIT observations exhibit an average standardized FCF of 2.28 percent, a median of 2.94 percent, and a standard deviation of 27.45 percent. The levels are similar to the full sample and all measures are statistically different from zero, which is also true of the full sample. The 148 firm-year mortgage REIT observations produce a mean of -2.13 percent, a median of 1.58 percent, and a standard deviation of 27.08 percent. The mean of the mortgage REITs is not statistically significant, computing a {\it p}-value of 0.34. The median and standard deviation measures are statistically significant.

In general, the REIT measures are significantly different than the RPFs in the Baker and Smith (2006) sample of non-REIT firms. And this finding holds for both equity and mortgage

REITs. Hence, based upon the standardized FCF measure, REITs do not exhibit a strict residual dividend policy.

3.3.2 Determinants of Dividend Policy

Since REITs demonstrate a less than strict residual dividend policy I next question if certain firm characteristics are significant in determining the dividend policy of REITs. To address the issue, I examine explanatory variables based upon the economic theory of investment opportunities, agency issues, asymmetric information, and profitability. Using existing theories and previous empirical studies of dividend policy within the financial economic literature, I examine the following model of REIT dividend behavior. Table 13 details summary statistics of the model variables.

Table 13: Summary statistics of REIT characteristics.

Variable	N	Mean	Median	Standard Deviation	Minimum	Maximum
$E_{i,t}/A_{i,t}$	1714	0.03	0.03	0.05	-0.44	0.78
Growth	1714	40.53	8.64	509.05	-93.34	20,701.09
Tobin’s Q	1573	1.03	1.02	0.37	-0.61	3.46
Slack	1712	0.03	0.01	0.05	0.00	0.58
Free Cash Flow	1628	18.62	7.94	109.76	-3,513.10	628.99
Ln(Assets)	1714	6.26	6.50	1.60	0.86	10.16
Leverage	1713	0.56	0.58	0.23	0.00	1.15
Dispersion	1617	0.00	-0.03	1.58	-4.63	4.17
Asset Turnover	1714	0.16	0.14	0.17	0.01	3.12
Change in Debt	1712	88.64	17.71	418.40	-1,508.21	10,385.57
Liquid Ratio	1591	7.66	0.78	50.15	0.00	1,397.01
Type	1714	0.91	1.00	0.29	0.00	1.00

Unlike previous studies of REIT dividend payout, the dividend payout dependent variable is not scaled by net income or shares outstanding, but instead, dividends are divided by contemporaneous total assets of the REIT. I employ this method for a number of reasons. First, as mentioned previously, scaling by total firm assets mitigates heteroscedasticity, which is not true of scaling by net income or shares outstanding. Second, scaling by total assets avoids the influential observation problem when earnings are near zero. Last, since I know that earnings have a significant effect on dividend payouts, and may be a proxy for investments in place, I want to empirically determine the effect of net income by controlling for it as a dependent variable.

The dividend payout results are presented in Table 14. The findings of the various models demonstrate that net income is an important determinant of REIT dividend payouts. This is to be expected as shown by many tests of the Lintner (1956) partial adjustment model in the finance literature, where models of dividend payments are usually restricted to contemporaneous net income and lagged dividends.[4] Also statistically significant and confirmed by numerous examinations of the Lintner (1956) model is the positive relation between lagged and contemporaneous dividend payouts. The positive relation between net income and dividend payments is also consistent with Bradley, et al. (1998), who split net income between the level of earnings lagged one period and the change in earnings.[5] They find a positive relation for both explanatory variables.

Table 14: Results of GLS regressions on unrestricted models of REIT dividend policy.

Explanatory Variable	Model 1	Model 2	Model 3
Intercept	0.04	0.05	0.05
	(4.94)	(5.07)	(4.59)
Earnings	0.72	0.71	0.72
	(26.75)	(26.25)	(26.54)
Lag(Dividends)	0.15	0.18	0.15
	(4.66)	(5.60)	(4.82)

table continued

[4] Tests of the Linter (1956) include Fama and Babiak (1968), Fama and French (2002), and Brav et al. (2005).
[5] Bradley, et al. (1998) use funds from operations as their measure of net income.

Growth (x10^{-6})	-3.73	-4.30	-3.77
	(-1.95)	(-2.20)	(-1.95)
Tobin's Q	0.01	0.01	0.01
	(2.40)	(2.62)	(2.58)
Slack	0.08	0.09	0.08
	(3.31)	(3.91)	(3.16)
Free Cash Flow (x10^{-4})	-0.46	-0.28	-0.42
	(-1.67)	(-1.09)	(-1.51)
Ln(Assets)	-0.01	-0.01	-0.01
	(-6.44)	(-6.52)	(-6.17)
Leverage	0.02	0.01	0.01
	(2.18)	(2.15)	(1.94)
Dispersion	0.00	0.00	0.00
	(1.22)	(0.82)	(1.04)
Asset Turnover	-0.00	-0.00	0.00
	(-0.16)	(-0.22)	(0.13)
Change in Debt	0.00	0.00	0.00
	(0.90)	(0.67)	(0.83)
Liquid Ratio	-0.00	-0.00	-0.00
	(-1.76)	(-1.75)	(-1.73)
Post 2000	-0.00	-0.00	-0.00
	(-1.37)	(-1.06)	(-0.32)
Type		-0.01	-0.01
		(-1.53)	(-1.57)
Year Dummies	No	No	Yes
R^2	0.44	0.44	0.44

One concern with the specifications in Table 14 is the simultaneous determination of REIT dividend policy with a number of the explanatory variables. For example, a REIT may borrow funds to pay a dividend and thus affect their leverage ratio in the same period. Hence, due to the endogeneity of dividend policy, the assumption that the independent variables and error term for each observation may not hold for the models in Table 14. To account for this issue, I utilize the alternative estimation method of instrumental variables (IV). I lag each variable one period with the exception of net income. In the numerous studies of the Lintner (1956) partial adjustment model, it is clear that contemporaneous net income is an important determinant of dividend payouts.

Table 15 details the results of the IV specification, again correcting for heteroscedasticity and autocorrelation. As expected, net income and the magnitude of the dividend payment last period continue as important determinants of REIT dividend policy. Another variable exhibiting some explanatory power is slack. Since slack is defined as cash scaled by total assets, the positive relation between slack and dividends suggests higher (lower) dividend payouts when more (less) cash is available. Initially, the amount of cash on hand affecting the level of dividend payout seems reasonable, but it is not entirely consistent with empirical studies of dividend reductions or the theory of dividend smoothing. Wang et al. (1993) show that equity REITs suffer a negative return when a dividend reduction is announced. Thus, a statistically significantly relation between cash and dividend payout is surprising since a reduction in cash implies a reduction in dividend.

Table 15: Results of GLS regressions using instrumental variables to explain REIT dividend payments.

Explanatory Variable	Model 1	Model 2	Model 3
Intercept	0.06	0.06	0.06
	(5.60)	(5.54)	(4.95)
Earnings	0.70	0.70	0.70
	(25.55)	(25.55)	(25.30)
Lag(Dividends)	0.18	0.18	0.18
	(3.49)	(3.42)	(3.13)
Lag(Growth)(x10^{-7})	2.97	2.91	3.20
	(0.20)	(0.19)	(0.21)
Lag(Tobin's Q)	0.00	0.00	0.00

table continued

	(0.67)	(0.96)	(0.73)
Lag(Slack)	0.04	0.04	0.04
	(1.84)	(1.76)	(1.57)
Lag(Free Cash Flow)	0.00	0.00	0.00
	(0.41)	(0.48)	(0.50)
Lag(Ln(Assets))	-0.01	-0.01	-0.01
	(-4.98)	(-4.95)	(-4.57)
Lag(Leverage)	-0.00	-0.00	-0.00
	(-0.31)	(-0.49)	(-0.42)
Lag(Dispersion)	0.00	0.00	0.00
	(0.32)	(0.22)	(0.23)
Lag(Asset Turnover)	-0.01	-0.01	-0.01
	(-0.83)	(-0.70)	(-0.75)
Lag(Change in Debt)	0.00	0.00	0.00
	(0.44)	(0.43)	(0.47)
Lag(Liquid Ratio)	0.00	0.00	0.00
	(0.49)	(0.52)	(0.56)
Post 2000	-0.01	-0.01	-0.01
	(-1.91)	(-1.86)	(-0.64)
Type		-0.01	-0.01
		(-1.17)	(-1.16)
Year Dummies	No	Yes	Yes
R^2	0.41	0.42	0.41

A variable that exhibits explanatory power in all the contemporaneous and IV specifications is the natural logarithm of total book assets. Since the dependent variable is already scaled by total book assets, this variable is not necessarily a proxy for the old standby of firm size. Instead, ln(assets) may be a proxy for volatility. This seems reasonable given the negative relationship, implying that highly volatile firms are more conservative with their dividend payout. Alternatively, Fama and French (2002) argue ln(assets) may proxy for firm age and ease of access to capital markets. If this is the case, I expect the relation to be positive since older firms are better known, thus, implying the ability to assess the capital markets more readily. Since the correlation between dividends and total book assets is negative, I are more inclined to accept ln(assets) as a measure of volatility.

With the exception of a dichotomous variable that accounts for a tax law change, the remaining explanatory variables are not statistically significant. This is consistent with the rationale that REITs mitigate agency and asymmetric information concerns. Additionally, the finding that free cash flow is insignificant is contrary to the pecking order hypothesis of Myers and Majluf (1984), which asserts that dividend payments are negatively affected by free cash flows. Also notable is that the change in debt is not significant using contemporaneous or instrumental variables, which is consistent with the Modigliani and Miller (1961) argument that debt is irrelevant to dividends payouts.

Model 3 includes dummy variables for each year of the sample period. There is no statistical impact on REIT dividend payouts in any of the individual years. However, the date that appears to be an important determinant in models 1 and 2 is the date of tax law change that went into effect on January 2001. Prior to this date, REITs were required to distribute 95 percent of their taxable income. Subsequently, the distribution requirement reduced to 90 percent. This negative coefficient on the dummy variable is consistent with the reduction in the required distribution.

3.3.3 Restricted Sample Based Upon REIT Type

Since Wang et al. (1993) find that REIT type is significant in three of the four sample years, I next split the sample between equity and mortgage REITs. The results are in Table 16. Model 1 of the equity REITs uses GLS, while model 2 uses two-way random effects. The mortgage REIT model uses GLS because there are not sufficient mortgage firm observations to compute two-way random effects or a GARCH model.

Table 16: Results of GLS using IV to explain dividend payments of equity versus mortgage REITs.

Explanatory Variable	Model 1	Model 2	Model 3
Intercept	0.04 (3.99)	0.04 (3.46)	0.04 (2.12
Earnings	0.87 (29.67)	0.82 (27.06)	0.04 (0.65)
Lag(Dividends)	0.05 (0.86)	0.23 (3.52)	0.80 (11.88)
Lag(Growth)	-0.00 (-0.04)	-0.00 (-0.19)	-0.00 (-0.16)
Lag(Tobin's Q)	-0.00 (-0.16)	-0.01 (-1.19)	0.00 (0.24)
Lag(Slack)	0.02 (1.02)	0.02 (0.65)	0.01 (0.17)
Lag(Free Cash Flow)	-0.00 (-0.65)	-0.00 (0.46)	0.00 (0.51)
Lag(Ln(Assets))	-0.00 (-3.18)	-0.00 (-2.88)	-0.00 (-0.77)
Lag(Leverage)	0.00 (0.61)	0.01 (0.83)	-0.01 (-0.89)
Lag(Dispersion)	0.00 (0.33)	0.00 (0.39)	-0.00 (-0.05)
Lag(Change in Debt)	0.00 (0.27)	0.00 (0.13)	-0.00 (-0.47)
Lag (Liquid Ratio)	0.00 (0.27)	-0.00 (-0.03)	0.00 (3.94)
Lag (Asset Turnover)	-0.01 (-1.21)	-0.00 (-0.65)	-0.06 (-1.03)
Post 2000	-0.01 (-1.77)	-0.00 (-1.45)	-0.01 (-1.60)
R^2	0.41	0.42	

The models examining the equity REITS are largely consistent with the full sample. The proxies for agency costs and asymmetric information are statistically insignificant, and net income and the natural logarithm of total firm assets continue to be determinants of REIT dividend policy. The differences in the equity models compared to the full model come in the significance of the level of dividends last period in model 1 and the dummy variable proxying for the tax law change in model 2. The standard error is basically the same for lagged dividends across both models. The difference between model 1 and 2 with respect to lagged dividends is the coefficient estimate. A coefficient of 0.05 on lagged dividends in model 1 is about the same magnitude of the standard error of 0.06, thus rendering the value statistically insignificant. I will examine this finding more closely in the next subsection to ensure the result meets with our prior intuition of dividend smoothing and target payouts.

The model for mortgage REITs seems to suffer from a small number of observations. The biggest indicator of a problem is the insignificant value for net income. This result is inconsistent with any of the empirical evidence using the Lintner (1956) partial adjustment model, and our prior intuition. The high R^2 and a dividend target payout of only 18 percent based upon the Lintner (1956) model of *Target Payout = Earnings/(1-Lagged Dividends)* are further evidence of model issues. An 18 percent target payout is not consistent with the REIT requirement of a 90 percent dividend payout.

3.3.4 Dividend Smoothing

The unrestricted specification in the previous section demonstrates that contemporaneous earnings, lagged dividends, firm volatility, the level of cash, and the REIT tax law change are determinants of REIT dividend policy. I next examine in more detail the Lintner (1956) partial adjustment model, which is a restricted specification utilizing only contemporaneous earnings and lagged dividends. The Lintner (1956) model gives us an understanding of REIT managers' ability to manage dividends through smoothing.

In a survey, Lintner (1956) finds that managers believe that shareholders prefer a steady stream of dividends, thus, firms tend to make periodic partial adjustments toward a target payout ratio rather than dramatic changes to payout. This relation is reflected as

$$D^*_{i,t} = r_i E_{i,t} , \tag{5}$$

where $D^*_{i,t}$ is the target dividends for firm *i* in year *t* and r_i is the firm's target ratio of dividends to after-tax earnings. According to the model, firms do not move immediately to a new target dividend, but instead smooth out changes in their dividends by moving part of the way to the target dividend each year. This leads to the follow equation,

$$\Delta D_{i,t} = a_i + c_i (D^*_{i,t} - D_{i,t-1}) + u_{i,t} , \tag{6}$$

where a_i is a constant, $0 < c_i < 1$ is a speed-of-adjustment (SOA) coefficient, and $u_{i,t}$ is a normally distributed random error term. Substituting (5) into (6) yields

$$\Delta D_{i,t} = a_i + c_i r_i E_{i,t} - c_i D_{i,t-1} + u_{i,t} , \tag{7}$$

which, in a multivariate regression setting leads to

$$\Delta D_{i,t} = \hat{\alpha}_i + \hat{\beta}_{1i} D_{i,t-1} + \hat{\beta}_{2i} E_{i,t} + \hat{u}_{i,t} , \tag{8}$$

where $\hat{\alpha}_i = a_i$, $\hat{\beta}_{1i} = -c_i$, and $\hat{\beta}_{2i} = c_i r_i$. Further, equation (7) can be rewritten as

$$D_{i,t} = \hat{\alpha}_i + \hat{\beta}_{1i} D_{i,t-1} + \hat{\beta}_{2i} E_{i,t} + \hat{u}_{i,t} , \tag{9}$$

where $\hat{\beta}_{1i} = 1 - c$, without affecting parameter estimates or the error term. The SOA and target payout ratio parameters provide a dividend smoothing measure because they are an indication of the level of the change in dividends that occurs in the short run in response to a change in the level of earnings. A higher value of *c* indicates a speedier adjustment or less smoothing.

Going back to the unrestricted model from the previous section, I use the Lintner (1956) model to initially examine dividend smoothing. Since the coefficients are same across the three models, the IV specification yields a SOA coefficient of 1 minus 0.18 = 0.82. Because the SOA ranges from total smoothing at zero and no smoothing at 1, the 0.82 factor indicates considerably reduced smoothing by equity and mortgage REIT managers.

I also compute the SOA for the samples split by REIT type in Table 16. The equity REITs demonstrate a SOA coefficient of 0.95 using GLS and 0.77 using two-way random effects. The magnitude of the SOA factor indicates that REIT managers conduct minimal smoothing.

The Lintner (1956) model also provides coefficients of TP. The full IV model in Table 17 computes a TP of 0.85, which is slightly below the 90 percent requirement. The GLS (model 1) specification in Table 14 produces a TP of 0.92, while the TP on model 2 is 1.06. The magnitude of both of these coefficients is consistent with the REIT tax law requirement, and the mean and median factors in Figure 6.

I next restrict the specification to the Lintner (1956) partial adjustment model – contemporaneous earnings and lagged dividend. Table 17 details the findings. Panel A presents the per share results, which is common practice for previous studies of the Lintner (1956) model. Panel B accounts for heteroscedasticity, and Panel C controls for heteroscedasticity and serial correlation.

Table 17: Restricted models using Lintner partial adjustment model to explain REIT dividend policy.

	Int	E_t	D_{t-1}	N	TP	SOA	R^2
Panel A: DPS and EPS							
Full Sample	0.44	0.27	0.54	1714	0.59	0.46	0.52
t-statistic	15.76	21.31	29.89				
Equity REITs	0.33	0.21	0.66	1559	0.60	0.34	0.68
t-statistic	15.95	20.63	43.43				

table continued

Mortgage REITs	0.68	0.35	0.42	155	0.60	0.59	0.39
t-statistic	3.84	6.52	6.15				
Panel B: Scaled by Total Assets							
Full Sample	0.01	0.60	0.38	1686	0.97	0.62	0.40
t-statistic	5.15	25.10	13.59				
Equity REITs	0.01	0.71	0.29	1536	1.00	0.71	0.41
t-statistic	4.46	26.98	9.72				
Panel C: Random Effects using Data Scaled by Total Assets							
Full Sample	0.01	0.72	0.21	1686	0.90	0.79	0.35
t-statistic	4.79	27.82	6.83				
Equity REITs	0.01	0.83	0.10	1539	0.92	0.90	0.39
t-statistic	4.47	30.30	3.22				

For the full sample of REITs in Panel A, the SOA is 0.46 and the TP is 0.59. The SOA is higher than the finding of 0.24 for REITs by Lee and Kau (1987). They also report earnings as an unimportant variable in forecasting dividend payments, which is contrary to studies of the Lintner (1956) model, and a TP of 0.50, which seems implausible given the 95 percent payout requirement during the 1971 to 1976 sample period. The smoothing factor of 0.46 for the full sample of equity and mortgage REITs is also higher than other studies of non-REIT firms. Lintner's original paper finds a SOA coefficient of 0.30, Fama and Babiak (1968) find an average of 0.37, Fama and French (2002) report a parameter of 0.33, and Brav et al. (2005) find a mean of 0.33 for all Compustat firms with valid data from 1984-2002.

The REIT TP of 0.59 is higher than the average of 0.22 for U.S. corporate firms illustrated in Figure 6. The TP is also higher than 0.33 result in Fama and French (2002), and the mean of 0.08 and median of 0.11 in Brav, et al. (2005). But while the TP is higher for REITs, the magnitude is not as high as that exhibited in Figure 6 or the 90 or 95 percent (depending upon the year of study) required by REIT tax law.

In addition to the full REIT sample, I execute the Lintner (1956) model on subsamples based upon type of REIT, the results of which are also in Panel A. The findings of the equity REITs are more in line with the non-REIT studies mentioned above. The lower SOA of 0.34 for equity REITs suggests that REIT managers conduct smoothing as much as other corporate firms. Alternatively, the SOA of 0.59 for mortgage REITs suggests less smoothing in these REITs.

The Lintner (1956) model assumes the elements of the random error vector are uncorrelated and have identical variances. However, Lagrange multiplier tests reject the hypothesis that the regression disturbances using per share data have constant variances. Thus, I scale the dividends in the restricted model by total book assets similar to the non-restricted specification. Scaling dividends by total assets removes the heteroscedasticity based upon Lagrange tests.

When scaled by total assets, the SOA coefficients increase significantly and the TP levels are consistent with the 90 percent payout requirement. The full sample SOA of 0.62 is almost twice the level of the previously mentioned dividend smoothing studies of non-REIT firms. Further, when REITs are broken into equity and mortgage REITs the equity REITs exhibit a higher SOA coefficient of 0.71. The findings indicate REIT managers manage their dividends but not to the extend of non-REIT managers.

Employing the Lintner (1956) model using data scaled by total assets helps remove heteroscedasticity, however, the model also assumes that the elements of the random error vector are uncorrelated across time. With the exception of Fama and French (2002), previous tests of the Lintner (1956) model do not appear to address the bias in the standard errors across time. Durbin (1970) tests for autocorrelation using dividends and earnings scaled by shares outstanding and total assets reject the hypothesis of no serial correlation of the disturbances across time periods. Hence, I next execute two-way random effects models following the Wansbeek and Kapteyn (1989) method for unbalanced panel data. Panel C of Table 17 illustrates the results.

Similar to Panel B, the earnings coefficient in Panel C using random effects increases significantly over the per share results. Because contemporaneous dividends are more sensitive to contemporaneous earnings, the SOA coefficient of the random effects model is 0.79 for the full model and 0.90 for the equity REIT subsample.[6] The level of the SOA coefficient indicates that REITs conduct minimal dividend smoothing. Also, consistent with tax law and the trend in Figure 6 is the TP using random effects. The full sample has a TP equal to the legal requirement of 90 percent and the equity REIT subsample is 0.92.

Overall, the Lintner (1956) model suggests that current earnings are much more important than dividends paid last period in determining current dividend payouts. One caveat to this general finding is that distinct patterns are easily noticeable in the raw data. The Lintner (1956) model may not pick up the systematic pattern since REITs are required to meet the payout requirement annually and yet most REITs pay a quarterly dividend. I examine quarterly dividend smoothing using the Lintner (1956) specification but do not note a major difference in the SOA coefficients to suggest more smoothing quarterly.

3.4 Chapter Summary

Although the 90 percent payout of taxable earnings by REITs initially appears to be quite constraining, prior real estate research demonstrates that certain REITs possess flexibility in their dividend payouts. Due to tax shields like depreciation, the gross cash flows of equity REITs, in particular, are materially different than the 90 percent payout of taxable earnings. Hence, I find that equity REITs are not strict residual policy firms, and that mortgage REITs follow a policy more closely resembling a residual policy, but not all measures indicate a strict residual policy.

[6] The mortgage REIT subsample does not produce valid results due to what appears to be a small number of observations (i.e., 22 firms over 11 years). Net income is not statistically significant, the TP is 0.50, and adjusted R^2 is 0.74, and the time series variance is negative. All of these factors are out of line with our prior intuition, prior research using the Lintner (1956) model, and current tax law.

I examine the determinants of REIT dividend policy, correcting for econometric problems that may cause problems with inferences in previous studies. I find that the two main determinants of REIT dividend payments are contemporaneous earnings and the level of dividends paid last period. These results are not surprising based on the numerous studies of the Lintner (1956) partial adjustment model in the finance literature. However, both of these results are different than existing literature on REIT dividend payouts.

I also find that the natural logarithm on total book assets and a tax law change are statistically significant in explaining dividend payments. Since many variables in the unrestricted specification are already scaled by total book assets to address heteroscedasticity, I argue that the negative coefficient on the log of assets is a proxy for firm volatility. The dummy variable for the tax law change denotes the change in required dividend payout from 95 to 90 percent.

Consistent with the arguments that REITs mitigate the market imperfections of agency costs and asymmetric information, I do not find proxies for Tobin's Q, growth, leverage, ownership dispersion, asset turnover, change in debt, or liquidity are significant determinants of REIT dividend policy. These results do not support other studies of REIT dividend policy. Instead, the findings promote REITs as a unique environment for testing of finance conundrums.

In the next chapter, I continue the examination of real estate investments that distribute current income. I investigate the real estate mortgage, which is a primarily vehicle for investors who desire quarterly payments. A major consideration of a mortgage investor is the prepayment and default of the underlying investment. In the next section, I describe the affect of credit scores on the prepayment and default options.

4. Credit Scores

Statistically based credit decision-making systems were pioneered during the late 1950s, but only saw mainstream use during the 1990s as the depth and breadth of electronic credit information increased.[7] These statistically based techniques are commonly referred to as credit scoring models. Initially, scoring models were employed in the consumer-credit portfolios of most major banks and credit card issuers to increase the speed of the credit decision, enhance the uniformity of the decision process, and reduce the overall costs of decision making. More recently, scoring models have migrated to other areas of the lending portfolio, particularly mortgages. In fact, the use of credit scoring models has become widespread in the mortgage-lending industry over the past 10 years. In addition to its use in the underwriting process, secondary mortgage market purchasers employ credit scoring as a means of pricing risk. These secondary purchasers include the government-sponsored enterprises of Fannie Mae and Freddie Mac, and private mortgage insurers.

Credit scoring is a significant factor in risk-based mortgage pricing since credit scores are a key predictor of credit risk. Indeed, if a borrower has a low enough credit score, other characteristics of the borrower and loan may not counteract the negative aspect of the credit score and the loan will be denied. Yet, as important as credit scoring is to the mortgage loan process, mortgage pricing models do not include credit scores as a stochastic state variable. Instead, previous theoretical and empirical studies treat credit scores as a transaction cost.

But the treatment of credit scores, or more specifically, the change in credit scores, as a transaction cost does not reflect the competing nature of credit scoring. On one hand, an increase in a borrower's credit score implies that the interest rate of a future mortgage will be less if the increase if enough to move into the next credit range. The higher credit rating increases the

[7] See Lewis (1994), "An Introduction to Credit Scoring'", for a history of credit scoring models.

likelihood of a borrower to prepay the existing loan. And, assuming the borrower values the increase in credit score, the likelihood of default will simultaneously decrease since the borrower will have less propensity to harm the new, higher credit rating. On the other hand, it is well established that the lower the credit score, the higher the rate of default. Simultaneously, a decrease in credit rating will promote the borrower to maintain existing financing since new financing will be more costly. This implies a decrease in the likelihood of prepayment.

Since the treatment of credit scores as a transaction cost does not reflect the true nature of the variable, I examine whether the two existing state variables in the mortgage option pricing model, house prices and interest rates, are sufficient to capture credit scores behavior. Using Pearson correlations, I find that the relations between the change in credit scores and the change in house prices and interest rates are not greater than the correlation between the two state variables. The magnitude of the correlation between house prices and credit scores is 0.07, between interest rates and credit scores is 0.16, and between house prices and interest rates is -0.10. Using univariate analysis I find that the change in credit scores is statistically significant in explaining the change in house prices, however, the adjusted R^2 of 0.01. Overall, house prices and interest rates are not adequate as proxies for credit scores.

Because the current two state variable mortgage pricing model is not highly correlated with credit score, I execute simulations using the pricing method of Hilliard et al. (1998) to determine the impact of changes in credit scores on the price of a mortgage. Following the method of Kau and Slawson (2002), I find a significant difference in the values of the mortgage asset from the lender's perspective, and mortgage liability from the borrower's perspective when prepayment and default vary simultaneously. The conclusion of the simulations is that changes in a borrower's credit score have a significant impact on the pricing of a mortgage.

The remainder of this chapter proceeds as follows. Section 4.1 summarizes credit scoring as it applies to mortgage issuance. Section 4.2 discusses the theory and empirical findings of credit rationing and its application to mortgage modeling. Section 4.3 describes the application of credit scores to mortgage pricing utilizing option pricing theory. Section 4.4 discusses the credit score data. Section 4.5 interacts credit scores with house prices and interest rates and simulates credit scoring in the option pricing model. Section 4.6 considers the spatial characteristics of credit scores. Section 4.7 summarizes this chapter.

4.1 Mortgage Credit Scoring

Credit scoring is widely used in mortgage origination. By one estimate, over 75 percent of all home mortgage loan decisions use credit scores as a significant factor in the decision-making process.[8] Both the Federal Home Loan Mortgage Corporation (Freddie Mac) and the Federal National Mortgage Corporation (Fannie Mae) encourage mortgage lenders to use credit scoring. In a letter dated July 1995 Freddie Mac promoted the use of credit scoring in loans submitted for sale to the agency. In a similar letter dated October 1995, Fannie Mae reported it was depending more on credit scoring for assessing risk.

Credit scoring utilizes data such as the applicant's outstanding debt and financial assets to determine a composite number based upon individual rating in the five categories: payment history (35 percent of the rating); length of credit history (15 percent); new credit (10 percent); types of credit used (10 percent); and debt (30 percent). Income is not a factor. Some mortgage models also use information about the property, such as real estate market conditions, and the loan, e.g., the loan-to-value ratio (see DeZube (1996)). According to Fair, Isaac and Company, Inc., a leading developer of scoring models, 50 to 60 variables might be considered when

[8] Testimony of Chris Larsen (E-Loan) before the U.S. House of Representatives' Committee on Banking and Financial Services hearing on "Credit Score Disclosure." (September 21, 2000).

developing a typical model, but eight to twelve probably end up in the final scorecard as yielding the predictive combination.

Regardless of the specific credit scoring system or specific variables utilized, the empirical evidence indicates that credit scoring assists in the mortgage loan process. A study by Freddie Mac found a high correlation between credit scores and loan performance on hundreds of thousands of mortgage loans. Additionally, the agency found a strong correlation between the underwriters' judgment and the Fair Isaac credit scores. Table 18 details statistics compiled by the mortgage industry concerning the composite credit score and mortgage loan delinquency ratios. Since lower credit scores result in a greater likelihood of delinquency, mortgage interest rates demonstrate a negative relation with credit scores. As of April 2006, Fair Isaac reports that a composite score between 760 and 850 will receive an interest rate of 6.13 percent, which is a monthly payment of $1,313 on a $216,000, 30 year, fixed-rate mortgage. In comparison, a borrower at the lower end of the spectrum, with a score between 620 and 639, with have an interest rate of 7.72 percent, which is a payment of $1,543 on the same $216,000 loan. Assuming the loan is kept to maturity, the difference in the total payment of the mortgage is $84,742 based solely on the credit risk of the individual.

Table 18: Credit Scores and Mortgage Loan Delinquency Ratios.

Credit Score	Odds of Becoming 90 Days Delinquent
780	576:1
700	288:1
680	144:1
660	72:1
645	36:1
630	18:1
615	9:1
600	4:1
585	2:1

Further empirical evidence in the real estate literature supports the use of credit scoring. Avery et al.(1996) find that credit scores based on the credit history of mortgage applicants generally are predictive of mortgage performance. The authors examine Equifax data for all outstanding mortgages whose payments were current. For each loan type (I.e., conventional fixed rate, conventional variable rate, or government-backed fixed rate) regardless of seasoning status (newly originated or seasoned), borrowers with low scores had substantially higher delinquency rates than those with medium or higher scores. They also examined data from Freddie Mac on loans for single-family owner-occupied properties. Their findings indicate that borrowers with low scores have higher foreclosure rates and that loans with both low credit scores and higher loan-to-value ratios have particularly high foreclosure rates. In addition, credit scores were much stronger predictors of foreclosure than was income.

4.2 Credit Rationing

The theory supporting the use of credit scoring in mortgage lending comes from credit rationing. Lenders ration credit through down payments and other underwriting mechanisms as opposed to allowing the loan rate clear the market. Stiglitz and Weiss (1981) argued that rationing by qualification standards is the result of imperfect information about the uncertainty surrounding the systematic credit risk of a loan application. They posit that moral hazard, adverse selection, and asymmetric information between lenders and borrowers regarding credit risk can cause equilibrium credit rationing. This can lead to lenders setting loan rates below market-clearing levels. Such an outcome arises because information is costly and lenders have an imperfect ability to classify borrowers according to default risk. Under such conditions, lenders price loans based on the expected return on the loan portfolio rather than the expected return of the individual loans. The expected return on the pool of loans, however, depends both on interest earnings on loan payments and on expected default costs. Each of these factors increase with the loan rate. In the latter case, as the loan rate increases borrowers have an incentive to invest in riskier projects (moral hazard) with higher expected returns. In addition, as loan rates rise, prospective borrowers with strong aversions to default tend to drop out of the applicant pool first (adverse selection), raising the average propensity to default of the remaining pool of borrowers. Competitive lenders respond to such effects by setting interest rates lower than would occur in the absence of moral hazard and adverse selection effects. Under such conditions, Stiglitz and Weiss (1981) show that it is possible that the competitive equilibrium will occur at below market-clearing interest rates.

Duca and Rosenthal (1991) provide empirical support for this theory in the mortgage market. Their model implies that lenders would not ration credit if they bore no default costs, suggesting that government-insured mortgages, which protect lenders from default costs, should be characterized by easier nonprice terms. Hence, the relative number of government-insured obligations should increase in periods of increasing default risk, as lenders tighten nonprice constraints on conventional loans. Duca and Rosenthal (1991) find that the FHA share of originations increases during periods of tight credit as some credit-constrained households switch from conventional to FHA financing. This is consistent with the theory since FHA loans are available to all households, but are more expensive than conventional mortgages. Using aggregate time-series data on mortgage originations and a default risk proxy, Duca and Rosenthal (1991) find empirical support for this hypothesis. It should be noted that although lenders typically require private mortgage insurance for loans with a down payment under 20 percent, mortgage insurers can deny insurance to applicants. Hence, mortgage insurance companies in conjunction with lenders can be viewed as rationing credit. Consistent with this view, foreclosure rates on conventional mortgages are generally much lower than those on FHA and VA loans.

4.3 Mortgage Pricing

Based on over twenty years of research, option theory has established itself as a foremost approach to pricing mortgages. Using this approach, a mortgage can be viewed as two derivative components: a prepayment call option and a default put option. At any time, a borrower can prepay the mortgage balance and in effect call the debt obligation. Two common methods of calling the mortgage are to sell the underlying real estate and to refinance the debt obligation. Conversely, if the value of the house is “out-of-the-money”, the borrower can put the property onto the mortgage holder. Complicating each of these options are features such as fixed- versus adjustable-rate mortgages, prepayment penalties, multiple stochastic state variables and transaction costs such as brokerage fees. Overall, mortgages are the topic of much finance and real estate literature.

4.3.1 Default

In the mid-1980s, Foster and Van Order (1984 and 1985), Epperson, Kau, Keenan, and Muller (1985), and Vandell and Thibodeau (1985) introduced the option-based model of default for mortgage pricing. Foster and Van Order (1984) were the first to apply option theory formally to the field of mortgage default by significantly extending the work of Campbell and Dietrich (1983). They estimate loan-to-value ratios over time and use this information to create a number of variables that represented the percentage of loans with negative equity for each year in the study period.

In general, the Foster and Van-Order (1984) option-based model of default works quite well. It explains over 90 percent of the variance using only equity variables. The authors find that borrowers do not exercise the default option consistently or ``ruthlessly", even with the assumptions of zero transaction costs and with negative equity.

Extending the work of Foster and Van Order are the studies by Epperson, et al. (1985) and Vandell and Thibodeau (1985). Epperson and associates utilize partial differentiation equations in a recursive model to examine default rate using simulated data. Vandell and Thibodeau execute a binary logit model with the dependent variable indicating the probability of default. In addition, Vandell and Thibodeau addressed the issues of transaction costs and crisis events. Unlike previous studies, Vandell and Thibodeau (1985) also consider the market value of the loan, as opposed to the book value, and use individual loan history data in their analysis. Lastly, they also consider the role of expectation in the default decision by modeling expected home values with a weighted index of backward-looking adaptive factors.

Overall, the theoretical premises by Foster and Van Order, Epperson and associates, and Vandell and Thibodeau constitute the basis for the current state of theory. The examination of the default decision as an option and the central role of net equity represent the dominant view in more recent default studies. The three studies also provide evidence about the importance of transaction costs and borrower-related factors such as expectations and occupation. Two real-world considerations are typically incorporated into contingent-claims mortgage termination models. The first is transactions costs of default, and the second is ``trigger events'' or exogenous termination such as job relocation.

4.3.1.1 Transaction Costs and Trigger Events

Default decisions incorporate transaction costs by adding a cost term to the outstanding balance at the time of default. Transaction costs include monetary moving costs, the associated social and family costs of a move, and financial disruption from a blemished credit standing or deficiency judgments that claim other assets. Transaction costs are usually modeled as a fixed dollar costs.

The importance of transaction costs in default is controversial. Foster and Van Order (1984) conclude that transaction costs must account for some of the results in their option based model because borrowers do not behave``ruthlessly". In general, the literature provides evidence against ruthless behavior, suggesting that default costs play an important role in borrower decisions.

Conversely, Kau, Keenan, and Kim (1994) developed an intertemporal optimization model of the default decision and contended that a borrower defaults, not when the value of the equity falls below the unpaid principal or the present value of the payments, but when it falls below the value of the mortgage to the lender. Consistent with Epperson et al. (1985), the authors show that this value includes both the value of exercising the option now and the value of terminating the option in the future. Using simulation analysis, the authors find support for their model. They demonstrate that the value of the house must fall by substantially more than the value of the mortgage's termination option at the point of zero equity before it is in fact rational for a borrower to default. The authors conclude that the amounts involved can be mistaken for transaction costs when in reality transaction costs play little or no role in the default decision. Kau, Keenan, and Kim (1994) point out that the default option is exercised only when house prices are well below the mortgage balance even if transaction costs are negligible. Lekkas, Quigley, and Van Order (1993) and Quigley and Van Order (1995) find differences in loan loss severity and reject the hypothesis that transaction costs do not matter.

In the context of an option pricing model, trigger events affect the optimal default decision by converting what is normally a multi-period optimization into a single period decision. Clauretie (1987) finds that the change in the unemployment rate is important. Quigley, Van Order and Deng (1994) find divorce explains higher default rates, but get mixed results regarding unemployment. Thomson (1994) finds both divorce and unemployment significant.

Overall, Capozza, Kazarian, and Thomson (1997) find transaction costs and trigger events are important to the default option. Additionally, Brueckner (2000) builds on the empirical literature designed to test the ruthless-default principle from option-based models of mortgage pricing. Brueckner (2000) takes a further step by arguing that such costs are private information. He adds asymmetric information between the borrower and lender to the transactions costs associated with default.

4.3.1.2 Insurance and Guarantees Against Default

If the occurrence of default can be calculated, it is no great feat to calculate values of insurance or guarantees against default. Cunningham and Hendershott (1984), Kau et al. (1990a, 1992, 1993), Kau, Keenan, and Muller (1993), and Schwartz and Torous (1992) consider this issue. There are two obvious ways to treat insurance: as an upfront lump sum payment or as part of the contract rate that determines monthly payments. Kau et al. (1992, 1993) take the former approach, though they note that the latter approach is included in their work, since obtaining the contract rate that balances the contract without insurance also encompasses the latter situation because the contract rate remains the same whether the lender chooses to purchase insurance or not.

4.3.2 Prepayment

There are two distinct classes of prepayment. The first type, endogenous payment, occurs as a result of the borrower's minimizing the market value of the loan (the market cost to the borrower). This financial prepayment is independent of the borrower's individual characteristics, and, in the absence of credit risk, depends only on the term structure. Such prepayment is generated in the contingent-claims models. The second type of prepayment occurs for extraneous reasons and does not minimize the objective cost of the mortgage. The motivation for such prepayment arises from the personal circumstances of the borrower, and, most commonly, involves the sale of a house with a non-assumable mortgage for such reasons as job relocation or change in family size.

Some of the earliest work on mortgage prepayment began with Dunn and McConnell (1981a, 1981b), Buser and Hendershott (1984), Brennan and Schwartz (1985), and Hall (1985). Dunn and McConnell (1981a, 1981b) are the first to apply the backward-solving model to fixed-rate default-free mortgages. They illustrate how the method developed by Brennan and Schwartz (1977) for nonamortizing bonds can be applied to the amortizing 30-year mortgages, and show the general implication of amortization. Buser and Hendershott (1984) examined the sensitivity of the simulated call values to the assumed parameters and valued 15-year level-payment mortgages and 30-year graduated-payment mortgages, as well as the standard 30-year level-payment mortgages. The pioneers of the application of numerical methods to the pricing of debt instruments, Brennan and Schwartz in 1985 turn their attention to pricing fixed-rate mortgages. They employed a two-state interest-rate model, which they contend leads to substantially more accurate pricing.

Dunn and McConnell (1981) build off Cox, Ingersoll, and Ross (1980), while Brennan and Schwartz (1985) work on Variable Rate Loan Contracts and the determinants of GNMA Mortgage Prices. Dunn and McConnell (1981b) introduces prepayment model into the contingent-claim framework as an external source of prepayments. The simplest means of doing this is to regard exogenous prepayments as an additional Poisson process, whose mean rate of arrival is then determined by the external prepayment model. Brennan and Schwartz (1985) follow this research method of introducing random prepayments as Poisson processes.

Cassidy (1983) and Dietrich et al. (1983) estimated the value of a partial offset to the call option - the forced prepayment of the mortgage when the house is sold. Cassidy (1983), using Monte Carlo simulation, computed the option to be worth 30 to 80 basis points. Dietrich et al., solving the partial differential equation backwards, reported somewhat higher estimates, 50 to 100 basis points.

Others, in addition to Brennan and Schwartz (1985) work with a two-state term structure. Schwartz and Torous (1989a, 1989b, 1991), Dale-Johnson and Langetieg (1986), and Dietrich and associates (1983) model fixed-rate mortgage. The advantage of the two-state process is that it provides more degrees of freedom in describing the actual term structure. The disadvantage is that it requires many more calculations to achieve a solution. Buser, Hendershott, and Sanders (1990) compare the one-state and two-state interest processes in the context of a mortgage and find the one-state form adequate. Conversely, Litterman and Scheinkman (1991) find one-state interest rate processes to be deficient in estimating the term structure. Schwartz and Torous (1992) examine prepayment and default but revert to a single state description of interest rates. One motivation for ignoring the role of default, and hence the houseprocess, is to free up computational power for simulating richer term structures.

4.3.3 Combining Default and Prepayment

The more recent advancements in the option-pricing approach to mortgage valuation combine default and prepayment into the same model. Since prepayment and default substitute for one another, contracts with only one of the default or prepayment provisions lead the borrowers to behave differently than when both are present. This substitution effect means that one cannot accurately value either the individual provisions or their interaction without modeling both options. Thus, solution of the Cox, Ingersoll, and Ross (1985b) model must include the borrower's two options to terminate before maturity. The prepayment option is American in style, with an inherent free boundary, and the default option is of compound European style (i.e., it is actually a series of options).

Seminal work on mortgage option pricing by Kau et al. (1992 and 1994) value a fixed-rate mortgage and its embedded option to default and prepay by adapting a two-state explicit finite-difference technique. The two-factor version of the option pricing model is based upon the value of the house, *H*, and the spot rate of interest, *r*. The term structure is from Cox et al. (1985), which is written as

$$dr = \gamma(\Theta - r)dt + \sigma_r \sqrt{r dz_r} \,, \tag{10}$$

where the spot rate of interest, *r*, drives the entire term structure, Θ is the long term mean rate of interest, γ is the speed of adjustment to the mean, σ_r is the standard deviation of the short rate, and dz_r is a Weiner process.[9]

The value of the house, *H*, is assumed to follow the Ito process

$$\frac{dH}{H} = (\alpha - s)dt + \sigma_H dz_H \,, \tag{11}$$

where α is the long-term mean growth rate of the house, *s* is the service flow, σ_H is the standard deviation of the value of the real estate, and dz_H is a Weiner process. Using risk neutrality arguments, *H* becomes

$$\frac{d\hat{H}}{\hat{H}} = (r - s)dt + \sigma_H dz_H \,. \tag{12}$$

Kau et al. (1992) show that under the perfect-capital-market assumption and the local expectations hypothesis that the partial differential equation is

$$\frac{1}{2}H^2 v^2 \frac{\partial^2 F}{\partial H^2} + \rho H \sqrt{r} v \sigma \frac{\partial^2 F}{\partial H \partial r} + \frac{1}{2} r \sigma^2 \frac{\partial^2 F}{\partial r^2} + \kappa(\Theta - r)\frac{\partial^2 F}{\partial r} + (r - \delta)H \frac{\partial F}{\partial H} + \frac{\partial^2 F}{\partial t} = rF \,, \tag{13}$$

[9] The equations and notation in this section are standard to those presented by Kau et al. (1992), Hilliard, Kau, and Slawson (1998), and Kau and Slawson (2002).

where ρ is the correlation coefficient between dz_r and dz_H. Standard arguments in finance allow us to write this process relating the asset value, F(r,H,t) to the state variables house price, H, and spot interest rate, r.

4.3.4 Competing Risks

A significant amount of work has been completed recently within a competing risk framework. The proportional hazard model introduced by Cox and Oakes (1984) provides a framework for considering the exercise of options empirically and the importance of other trigger events in mortgage terminations. As described in Deng, Quigley, and Van Order (2000), the approach estimates the competing risks simultaneously, and accounts for the fact that risks may be correlated.[10] The competing risks model for mortgage prepayment and default is similar to the context of corporate finance and contingent claims literature with borrowers viewed as equityholders and lenders as debtholders. Ultimately, the log likelihood function of the competing risk model is given by

$$\log L = \sum_{i=1}^{N} \delta_{pi} \log(F_p(K_i)) + \delta_{ui} \log((F_u(K_i)) + \delta_{ci} \log((F_c(K_i)) ,$$

where $\delta_{ji}, j = p, d, u, c$ are indicator variables that take the value of one if the ith loan is terminated by prepayment, default, unknown type, or censoring, respectively, and take a value of zero otherwise.

Deng, Quigley, and Van Order (1996) utilize the competing risks model when analyzing a sample of low-down payment mortgages that default. In this model, prepayment and default are considered interdependent competing risks. Further, Deng, Quigley, and Van Order (2000) model default and prepayment as dependent competing risks to effectively examine the joint nature of the put and call options. Strong support is found to suggest that the value of the put

[10] Deng, Quigley, and Van Order follow the econometric process given by Han and Hausman (1990), Sueyoshi (1992), and McCall (1996).

(call) has a significant effect on the call (put) risk. The discrete specification of unobserved heterogeneity allows borrowers to be differentiated into groups based on relative riskiness. In terms of prepayment, the high-risk group is found to be approximately three times riskier than the intermediate group and twenty times riskier than the low risk group. For default, however, borrowers are found to be rather homogeneous. This is partly due to the fact that defaults on residential mortgages are rare events because of incomplete separation of investment and consumption decision in housing as well as the high costs of default on personal credit. The authors attribute the significance in exercising mortgage options or differences in borrowers' sophistication in exercising mortgage options or differences in levels of unobserved transaction costs. However, unobserved heterogeneity may also capture the measurement errors in option values and observable transaction costs.

Clapp, et al. (2001) model competing risks of mortgage termination where the borrower faces a repeated choice to continue to pay, refinance the loan, move or default. Most previous empirical work on mortgage prepayment ignores the distinction between prepayments triggered by refinancing and moving, combining them into a single prepayment rate. They show that financial considerations are the primary drivers of the refinance choice while homeowner characteristics have more influence on the move decision.

4.4 Credit Scoring Data

4.4.1 Credit Scores

To examine the impact of the competing transaction costs of changes in credit score related to mortgage pricing, I use proprietary data from TransUnion, a provider of credit scoring services. TransUnion provides de-personalized aggregated time series credit information, from which this chapter utilizes the median aggregate credit score for each state in the contiguous U.S. plus

Washington D.C. The data spans the fourth quarter of 1998 to the first quarter of 2004, resulting in 1078 state-quarter observations.

Table 19 details the summary statistics of the data. As might be expected, credit scores are autocorrelated. Therefore, I use the change in credit scores to compute the findings of this study. I examine autocorrelation for up to five quarterly periods to ensure that seasonal periods do not affect the results. I find that the autocorrelation is of degree AR(1), thus using changes is sufficient. As a robustness check of our results, I use the raw numerical change in the credit scores as well as a percentage change. Table 19 refers to these variables as CS-RChange for raw numerical change and CS-PChange for percentage change.

Table 19: Credit scoring summary statistics.

Variables	N	Mean	Standard Deviation	Median	Minimum	Maximum
Credit Score	1078	687.740	32.098	690.000	599.000	745.000
CS-RChange	1029	-0.017	5.187	0.000	-27.000	24.000
CS-PChange	1029	-0.000	0.008	0.000	-0.038	0.035
House Price	1078	248.125	67.291	235.450	139.480	616.300
HP-RChange	1029	4.002	3.600	2.900	-2.930	28.880
HP-PChange	1029	0.015	0.010	0.013	-1.012	0.068
Interest Rate	22	6.894	0.848	6.923	5.507	8.320
IR-RChange	21	-0.055	0.324	-0.150	-0.633	0.590
IR-PChange	21	-0.008	0.048	-0.022	-0.083	0.092

4.4.2 Other State Variables

One of the objectives of this chapter is to examine the impact of credit scores on house prices. Therefore, I obtain quarterly house prices from the Office of Federal Housing Enterprise Oversight (OFHEO) for each state. The index is based upon the first quarter of 1980 equal to 100. Therefore, as seen in Table 19, the average house price has appreciated approximately 2.48 times from the first quarter of 1980 to first quarter of 2004. Table 19 also provides the numerical

(HP-RChange) and percentage (HP-PChange) changes in house prices.

Another objective of this essay is to examine the impact of credit scores on interest rates and vice versa. I use interest rates from Freddie Mac fixed-rate 30-year conventional mortgages. Again, I use the numerical and percentage changes for computations. Table 19 details the summary statistics for the interest rates measures.

4.5 Modeling Credit Scores in Mortgage Pricing

Whether through the use of an option pricing model (OPM) or competing risks model, mortgages are priced considering the two embedded options of default and prepay by adapting a two-state explicit finite-difference technique. Kau and Slawson(2002) discuss the fact that the contingent claims and competing risk models answer the question of mortgage pricing from two directions. Whereas, the competing risk models address the empirical data to find the correct pricing model, option pricing models (OPMs) attempt to build the correct model through the correct usage of economic inputs. One of the major sticking points seems to be that mortgage borrowers are more heterogeneous than is allowed by OPMs. However, theoretical OPMs can accommodate borrower heterogeneity, and can simulate the value implications of non-financial decisions while preserving financial decisions. Hence, I leverage off the work of Kau and Slawson (2002) and Hilliard, Kau, and Slawson(1998). These papers show that the OPM can be crafted such that heterogeneities can be modeled and the appropriate mortgage price can be obtained.

In addressing a mortgage borrower's heterogeneity, the foremost topic emphasized is transactions costs associated with either default or prepayment. A list of transactions costs include: the time and effort expended in searching, pricing, and evaluating alternative properties; real estate brokerage fees; mortgage broker or banker fees, such as discount points; appraisal costs; attorney fees; prepayment penalties; moving costs; and loss of reputation associated with the decline of a borrower's credit score. Analysis of these transactions costs yields one important distinction that is not addressed in previous studies, namely, that credit scores are unique in that they affect both prepayment and default simultaneously.

The other transaction costs do not appear to be competing. If the time and effort expending in searching, pricing, and evaluating alternative properties increases(decreases), a mortgage borrower will have an decreased(increased) likelihood of prepaying the mortgage, all else equal. Similarly, if brokerage fees, mortgage banker fees, appraisal costs, attorney fees, and moving costs increase(decrease), a borrower experiences a decrease(increase) in incentive to prepay the existing mortgage because the transactions costs of purchasing a new property and moving have risen(declined).

In contrast to these other transaction costs, any change in a borrower's credit rating affects the price of a mortgage on both the prepayment and default options. On one hand, an increase in a borrower's credit score implies that the interest rate of a future mortgage will be less, which increases the likelihood of a borrower to prepay the existing loan. And, assuming the borrower values the increase in credit score, the likelihood of default will simultaneously decrease since the borrower will have less propensity to harm the new, higher credit rating. On the other hand, it is well established that the lower the credit score, the higher the rate of default. Simultaneously, a decrease in credit rating will cause the borrower to maintain existing financing since new financing will be more costly. This implies a decrease in the likelihood of prepayment.

4.5.1 Correlations

As a precursor to what could potentially be a three-state explicit finite-difference model, I initial examine the correlations between the three state variables. Table 20 details the correlations of the two types of changes (numerical and percentage) of the state variables. The results are consistent for both types.

Table 20: Pearson correlation coefficients of changes in credit scores, house prices, and interest rates.

	CS-RChange	CS-PChange	HP-RChange	HP-PChange	IR-RChange	IR-PChange
CS-RChange	1.000					
CS-PChange	0.999	1.000				
HP-RChange	0.066	0.065	1.000			
HP-PChange	0.091	0.090	0.930	1.000		
IR-RChange	0.164	0.168	-0.106	-0.117	1.000	
IR-PChange	0.155	0.160	-0.096	-0.101	0.992	1.000

The results for credit scores and house prices in the first and second column indicate correlations between 0.065 and 0.091. While all the correlations in Table 20 are significant at the 5 percent level, the lower level of correlation implies that house prices do not alone address the increasing importance of credit scores.

The same can be said concerning the interaction of credit scores and interest rates. The correlation is within the range of 0.155 to 0.168. Again, the correlation is significant, but is not nearly high enough to discount the use of credit score in an OPM.

The last item of note on Table 20 is the correlation between interest rates and house prices. The range is between -0.117 and -0.096. This is similar to the magnitude of the correlation between credit scores and the other two state variables. Hence, following the history of including house prices and interest rates in the OPM, the correlation results do not preclude credit scores from inclusion in the OPM.

4.5.2 Regressions

I also examine the interaction among house prices, credit scores, and interest rates by using ordinary least squares (OLS) to regress combinations of the numerical and percentage changes of credit scores and interest rates on the percentage change in house prices. Table 21 details the findings. The results demonstrate that changes in credit scores are a statistically significant explanatory variable, both alone and in concert with changes in interest rates, the coefficient of determination is rather low.

Table 21 OLS regression models to examine house price changes using changes in credit scores.

Variable	(1)	(2)	(3)	(4)
Intercept	0.02	0.02	0.01	0.01
	(47.71)	(47.72)	(46.76)	(46.69)
CS-PChange	0.12		0.15	0.15
	(2.90)		(3.49)	(3.62)
CS-RChange		0.00		
		(2.94)		
IR-PChange			-0.03	
			(-3.78)	
IR-RChange				-0.00
				(-4.34)
Adjusted R^2	0.01	0.01	0.02	0.03

To confirm these results, I compute additional OLS models using various combinations of credit scores and interest rates as well as some well-known explanatory variables of house prices. The models in Table 22 control for median household income(Income), the state population over 16 that is employed(Employment), the percentage of population with a college degree or higher(College), the average number of rooms in a home(Rooms), the average age of a home(AGE), and the proportion of the population that is under age 16 (YOUNG) and over 65(OLDER). The inclusion of these variables does not change the magnitude of the coefficients on credit scores and interest rates, but does reduce the standard error, thus increasing the {\it t}-statistics. Additionally, the coefficient of the intercept is dramatically reduced, and the coefficient of determination increases materially.

Table 22: OLS regression models to explain house prices using credit scores and other hedonic variables.

Variable	(1)	(2)	(3)	(4)

table continued

Intercept	0.04	0.04	0.04	0.04
	(0.42)	(0.43)	(0.42)	(0.42)
CS-PChange	0.14		0.14	
	(4.11)		(3.95)	
CS-RChange		0.00		0.00
		(4.19)		(4.03)
IR-PChange			-0.03	-0.03
			(-4.52)	(-4.52)
IR-RChange	-0.00	-0.00		
	(-5.19)	(-5.19)		
Income	0.00	0.00	0.00	0.00
	(7.11)	(7.12)	(7.09)	(7.10)
Employment	-0.00	-0.00	-0.00	-0.00
	(-0.82)	(-0.82)	(-0.81)	(-0.81)
College	0.00	0.00	0.00	0.00
	(4.89)	(4.89)	(4.88)	(4.88)
Rooms	-0.01	-0.01	-0.01	-0.01
	(-6.20)	(-6.20)	(-6.17)	(-6.18)
Age	-0.00	-0.00	-0.00	-0.00
	(-0.22)	(-0.22)	(-0.22)	(-0.22)
Young	-0.03	-0.03	-0.03	-0.03
	(-2.22)	(-2.23)	(-2.22)	(-2.22)
Older	0.06	0.06	0.06	0.06
	(3.48)	(3.48)	(3.47)	(3.47)
Adjusted R^2	0.33	0.33	0.33	0.33

4.5.3 Simulations

To see how the competing transaction cost affect mortgage prices, I simulate results using the pricing method of Hilliard et al. (1998). Their model approximates the prepayment and default option values in the event of frictions, such as transaction costs. The method is a backwards-pricing numerical procedure based upon the multivariate binomial option pricing technique in Nelson and Ramaswamy (1990). Hilliard et al. (1998) utilize the method of Nelson and Ramaswamy (1990) to create a computationally simple bivariate binomial tree of house prices and interest rates. After accounting for the various boundary conditions imposed by the borrower who acts to minimize the mortgage liability in the face of frictions at each decision point in the tree, the technique approximates the option values, *f*, in the partial differential equation in equation (13). The option value are then used in the mortgage valuation

$$V_{t,r,H} = RP_{t,r} - C_{r,t,H} - P_{t,r,H},$$

where $RP_{t,r}$ is the value of the remaining payments at time *t* given the level of *r*, $C_{r,t,H}$ is the prepayment(call) option value at time *t* given *r* and *H*, and $P_{t,r,H}$ is the default(put) option value at time *t* given *r* and *H*.

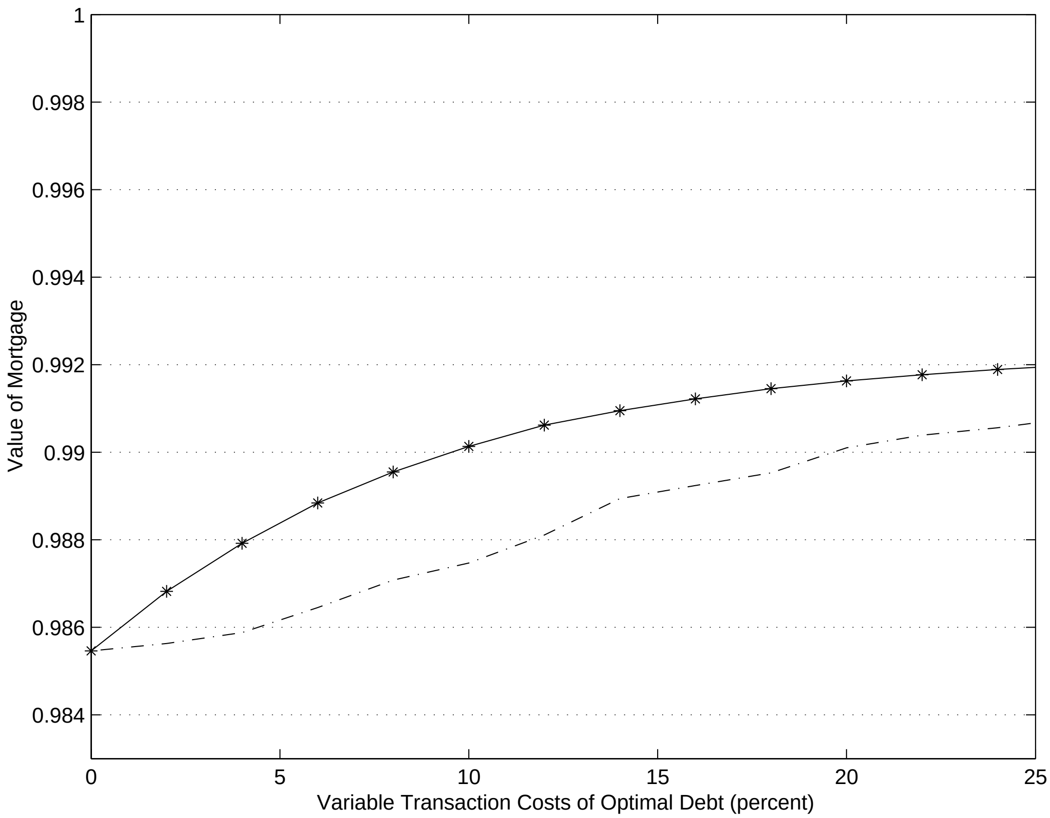

Figure 7: Kau and Slawson (2002) simulation results.

To begin the simulation I create the base case of Kau and Slawson (2002). The parameters of the Cox et al. (1985) interest rate process in equation (10) are r_0 =10 percent, σ_r =10 percent, Θ = 15 percent, and γ =25 percent. The house price parameters in equation (12) are σ_H =15 percent and *s* = 8.5 percent. In addition, the loan-to-value ratio at origination is 80 percent and the contract rate is 12 percent. Using these parameters yields Figure 7. The initial value of the mortgage, $V_{t,r,H}$, is equal to 0.98546, which means that for a $100,000 home with an $80,000 mortgage, the initial value of the mortgage given the prepayment and default option equals 78,836.80.

Kau and Slawson (2002) compute the values shown in Figure 7 for various values of *Variable Transaction Costs of Optimal Default*. In their study, the authors argue that an OPM can allow for any transaction costs and simulate their inclusion as shown in Figure 7. In their friction example, generic transaction costs increase in an optimal manner for default. They show that when transaction costs are between 0 percent and 12 percent, the put option of the liability is always greater than the put option on the asset.

Using the Kau and Slawson (2002) model, I simulate the competing transaction cost of credit scores. I begin with a base case using some of the same parameters as in Figure 7 - r_0 =10 percent, σ_r =10 percent, Θ = 15 percent, γ =25 percent, σ_H =15 percent, s = 8.5 percent., loan-to-value ratio at origination is 80 percent, and the contract rate is 12 percent. Instead of modeling optimal default only, I allow prepayment and default to vary simultaneously. Figure 8 shows the results. The mortgage asset findings represent the lender's perspective, and the mortgage liability results represent the borrower's perspective.

The Kau and Slawson (2002) base case begins at the 4 percent mark. The value of the liability is 1.01562 while the value of the asset is 0.98672. These values equate to $81,249.60 and $78,937.60 for the example of an $80,000 mortgage. As a borrower's credit score increases, the transaction cost of prepayment decreases, which is the x-axis. Under this simulation, prepayment costs decrease to 3 percent, while costs associated with default increase to 6 percent. The resulting value of the liability is 1.00987 and the asset is 0.98628. Further values are computed for 2 percent prepayment costs with 7 percent default costs and 1 percent prepayment costs and 8 percent default costs. The results indicate that the value of the liability is always greater than the value of the asset.

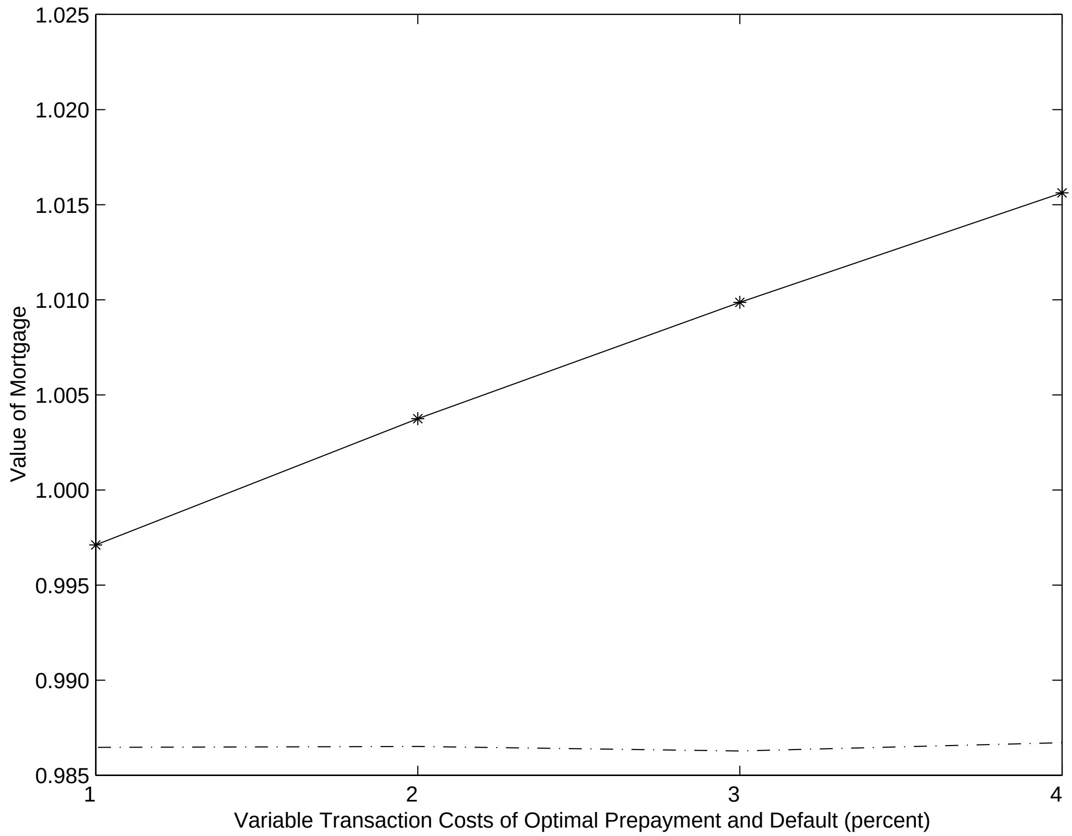

Figure 8: The effect of increasing credit scores on the lender's mortgage asset and the borrower's mortgage liability

To examine the affects of decreasing credit scores, I re-executed the Kau and Slawson (2002) model, beginning with the base case and raising prepayment costs from 4 percent to 5, 6, 7, and 8 percent. The comparable default costs begin at 5 percent and reduce from 4 to 1 percent. Figure 9 displays the results of the simulation. Again, the base case of 4 percent prepayment and 5 percent default yields a liability value of 1.01562. This amount increases to 1.02074 for 5 percent and continues to increase up to 1.03242 for 8 percent prepayment costs with 1 percent default costs. The associated asset value begins at .98672 and increases to 0.99348.

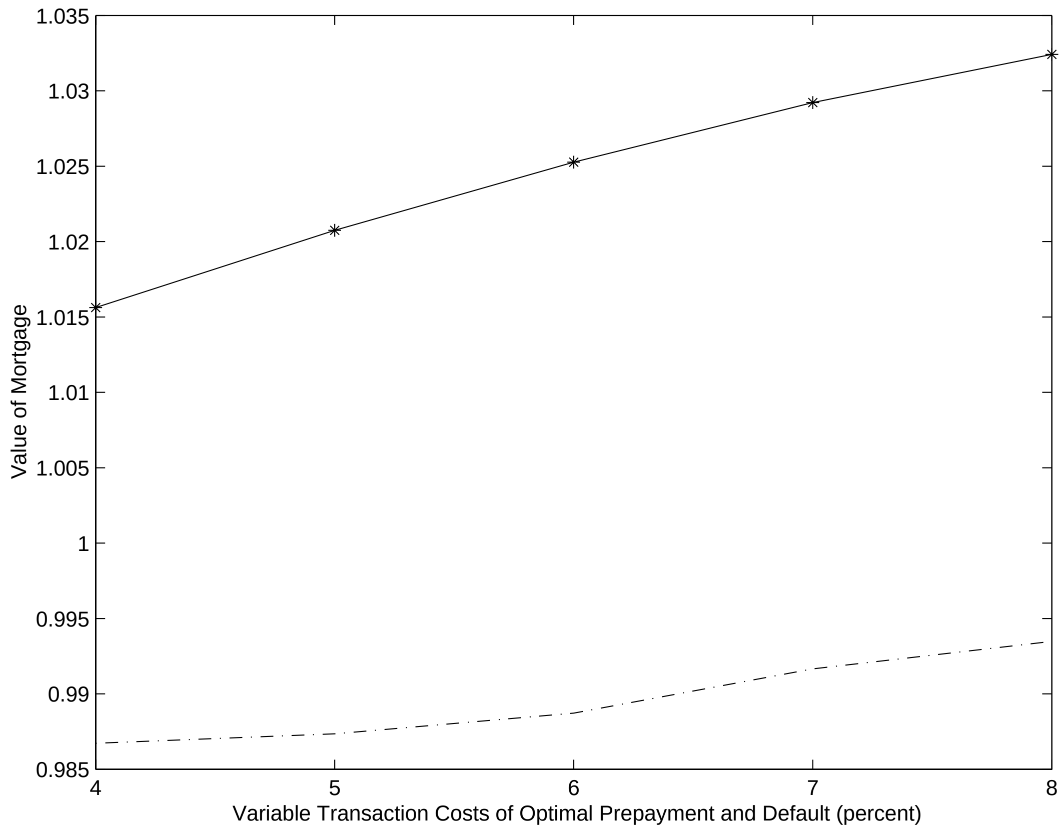

Figure 9: The effect of decreasing credit scores on the lender's mortgage asset and the borrower's mortgage liability.

The simulations demonstrate that when transaction costs associated with the prepayment and options vary simultaneously, the price of a mortgage changes for both the lender and borrower. A question arises as to the correct method to account for the change. One method may be to incorporate the competing transaction cost into the existing mortgage OPM. However, given the importance of credit scoring to the mortgage industry, it seems that the best method is to incorporate credit scoring as an additional state variable.

4.6 Spatial Considerations

To incorporate credit scoring as a state variable in the mortgage OPM, one must understand the behavior of credit scores. While this exercise is not within the scope of this essay, I include one aspect of credit score behavior that should be included in any modeling. Namely, credit scores are not only correlated across time, but across space. Using just the median credit score of each state in the continental U.S., Figure 10 details how credit scores cluster into regions.

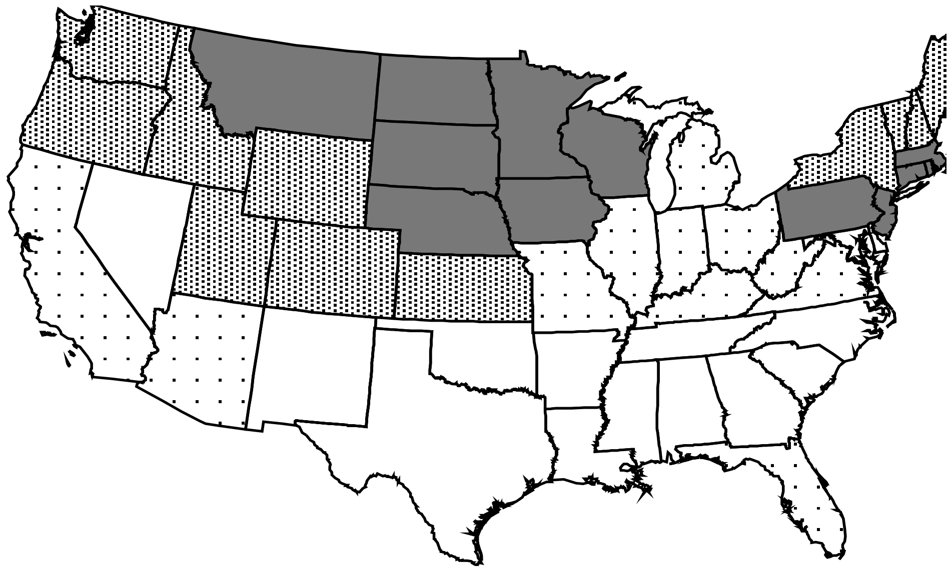

Figure 10: Quartile credit score by state.

Little is written in the literature regarding the spatial aspect of credit scores. Searches on JSTOR, Lexis-Nexis, EBSCO did not yield one referred journal article on the topic. The only reference to the spatial considerations of credit scores is from Avery et al (2000), who examine the determinants of credit scores, and include nine Census regions. They find that six of the regions are statistically significant, which is consistent with Figure 10. In the figure, white is the lowest quartile, infrequent dots the second quartile, heavy gridding is the third, and dark gray is the highest quartile.

To assess the significance of spatial correlation, I use the generalized least squares (GLS) model, defined as $Y = X\beta + U$, where U is a zero-mean vector of errors with variance-covariance matrix C such that $E(U)=0$ and $E(UU^T)=C$.

As described by Bailey and Gatrell (1995), the GLS model is specified interactively through relationships between explanatory variables and their neighboring values. One simple variate interaction model is

$$Y = X\beta + U$$

$$U = \rho WU + \varepsilon$$

where ε is a vector of independent random errors with constant variance σ^2 and W is a proximity matrix. This model is an example of a spatial autoregressive model (SAR), in this case with just one interaction parameter ρ . The model is

$$Y = X\beta + \rho WU + \varepsilon$$

$$= X\beta + \rho W(Y - X\beta) + \varepsilon$$

$$= X\beta + \rho WY - \rho WXB + \varepsilon$$

Hence, Y is expressed as a response to several influences; Y_i in state area A_i depends on the surrounding value for $Y_j (j \neq i)$, through the term ρWY ; it also depends on the general trend through $X\beta$; and on neighboring trend values through $\rho WX\beta$.

Table 23 details the coefficients and signed root deviances. The signed root deviances can be interpreted as *t*-statistics. The SAR model finds that with credit scores as the dependent variable, holding a college or higher degree, the number of rooms in a home, the proportion of the population over age 65, and space, as denoted by ρ , are statistically significant. While modeling credit scores in the mortgage OPM requires extensive work, Table 23 demonstrates that the spatial correlation of credit ratings must be included as part of the modeled behavior.

Table 23: Spatial-temporal models of credit scores.

Variables	Beta Estimates	Signed Root Deviances	PR of Higher SRDS
Intercept	11.5792	1.5816	0.1137
Income	0.0398	-1.1459	0.2518

table continued

Employment	0.1698	1.7839	0.0744
College	0.0826	3.5476	0.0004
Rooms	0.2267	3.9311	0.0001
Age	0.7775	0.7973	0.4253
Young	0.0663	-1.6011	0.1094
Older	0.1597	4.5197	0.0000
Population	0.0062	1.9664	0.0493
ρ	0.8460	5.7548	0.0000

4.7 Chapter Summary

This chapter examines credit scores and their application to mortgage pricing. Over the past 10 years credit scores have become a fundamental part of the mortgage origination process. In addition to its use in the underwriting process, secondary mortgage market purchasers employ credit scoring as a means of pricing risk.

Current models of mortgage pricing model credit scores as a transaction cost that is either increasing or decreasing, but not both. However, a change in credit scores effects both the prepayment and default option of a mortgage simultaneously. If a borrower's credit score increases, the transaction costs associated with the prepayment option will decrease, and the transaction costs associated with default will increase. Alternatively, if a borrower's credit rating decreases, the prepayment transaction costs increase, while the default costs will decrease. Simulations in this chapter find that when competing transaction costs are allowed to vary, the price of a mortgage significantly changes.

Instead of treating credit scores as a competing transaction cost, the better treatment is to add credit scores as a stochastic state variable in a contingent claim model. This is especially true given the increasing importance of creditworthiness in loan origination and the secondary mortgage market. The results in this essay demonstrate that credit scores are not highly correlated with house prices and interest rates, thus, there inclusion will make for a better mortgage pricing model.

5. Conclusion

The findings from this dissertation present new understanding to the field of real estate. Due to heterogeneity and immobility, the results demonstrate a concern for large-scale real estate portfolios like the type used by pension funds and insurance firms. For large-scale real estate investments, REITs, used by individuals to generate income, the findings shed new light on the determinants of dividend policy, and market imperfections inherent to REITs. Finally, for real estate investors who prefer mortgage income, the results demonstrate a need to include credit scores in the mortgage pricing models.

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Vita

Darren Hayunga earned his Bachelor of Science degree in business with a major in finance and a minor in real estate from Western Illinois University. Upon graduation and after gaining a couple years of business experience, he opened a financial planning practice in Frederick, Maryland. After five years of private practice, Mr. Hayunga closed his firm and went on to earn his Master of Business Administration degree from The College of William and Mary. Thereafter, he joined the information technology (IT) field as a consultant. After working as an IT consultant for five years, Mr. Hayunga decided to return to academia, and joined the finance doctoral program at Louisiana State University. During his doctoral study, he taught real estate and finance classes and conducted a number of research projects. The general area of his research interest is real estate finance. Most recently, Mr. Hayunga accepted an assistant professor position at the University of Texas at Arlington, starting August 2006.